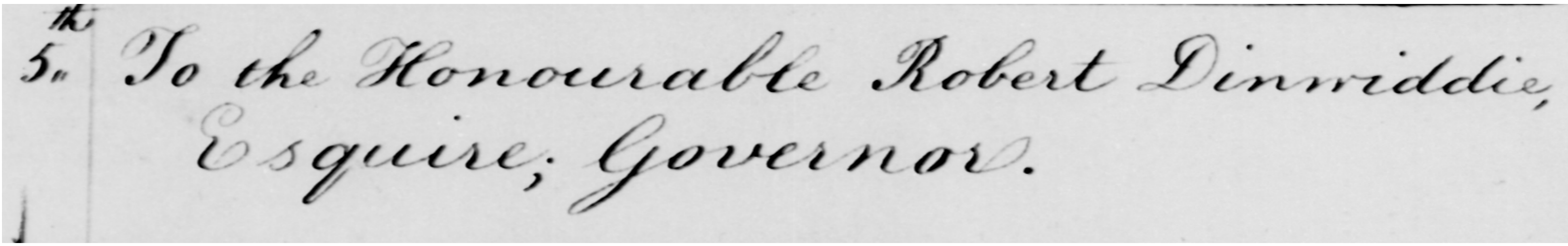
Part-Structured Inkball Models for One-Shot Handwritten Word Spotting

Nicholas R. Howe

Smith College

Word Spotting (by Example)


5th To the Honourable Robert Dinwiddie,
Esquire; Governor.

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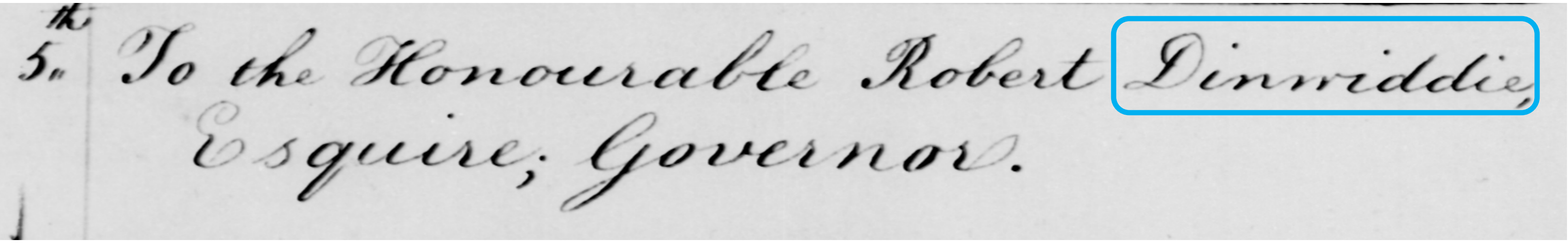
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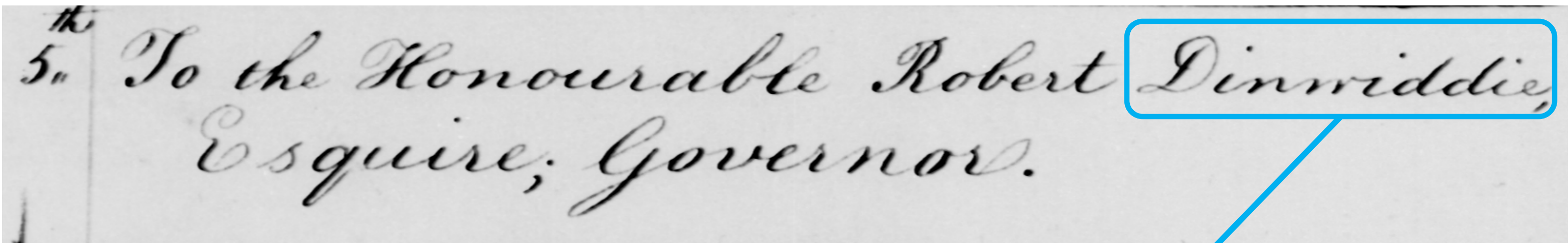
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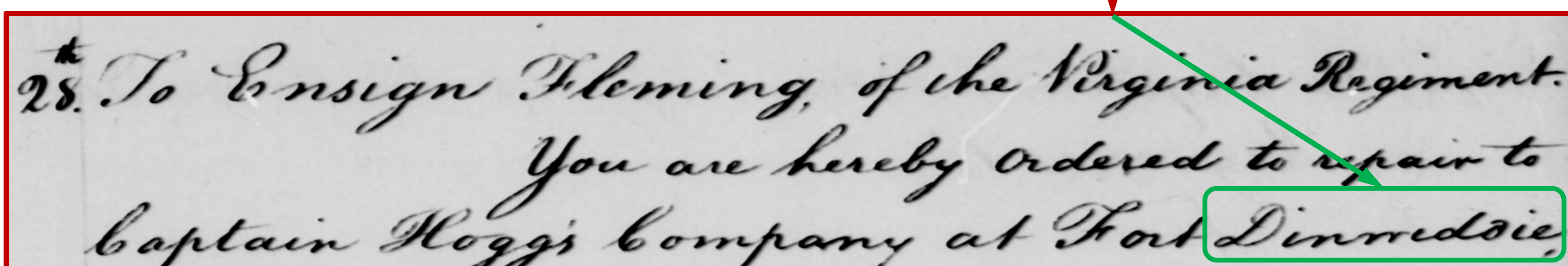
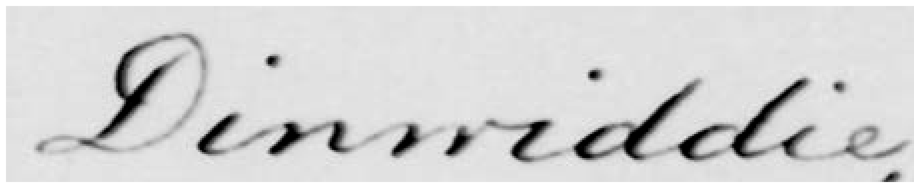

28th To Ensign Fleming of the Virginia Regiment.
You are hereby Ordered to repair to
Captain Hogg's Company at Fort Dinwiddie

… etc.

One-Shot Learning

Single example is all you get (usually)



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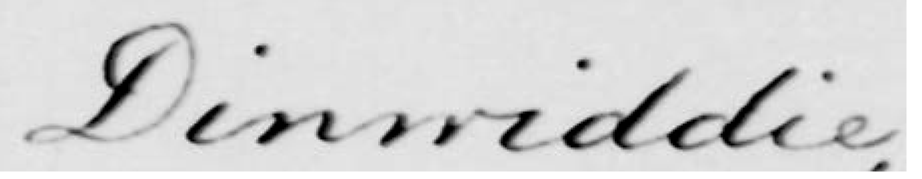
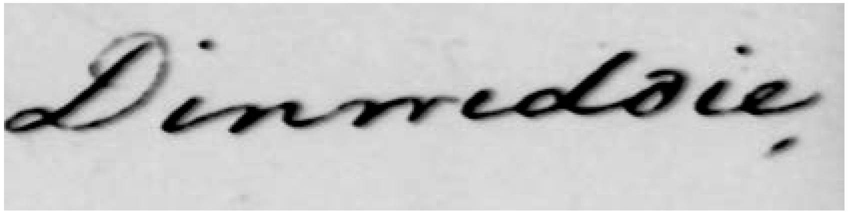


Handwriting varies – must generalize to match



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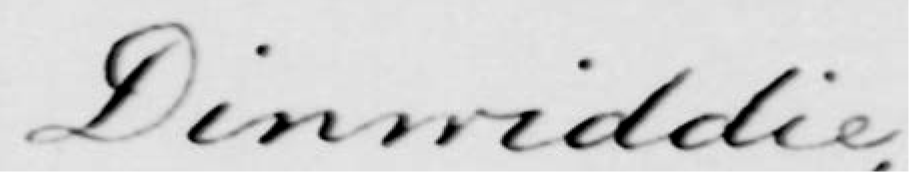

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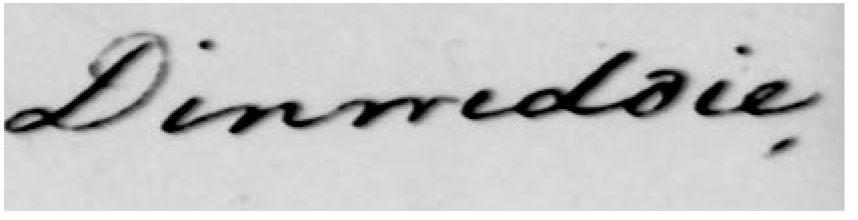

Flexibility is essential – no planar transformations

Part-Structured Models

- Used for photographic object recognition
- Detected parts arranged in approximate spatial configuration

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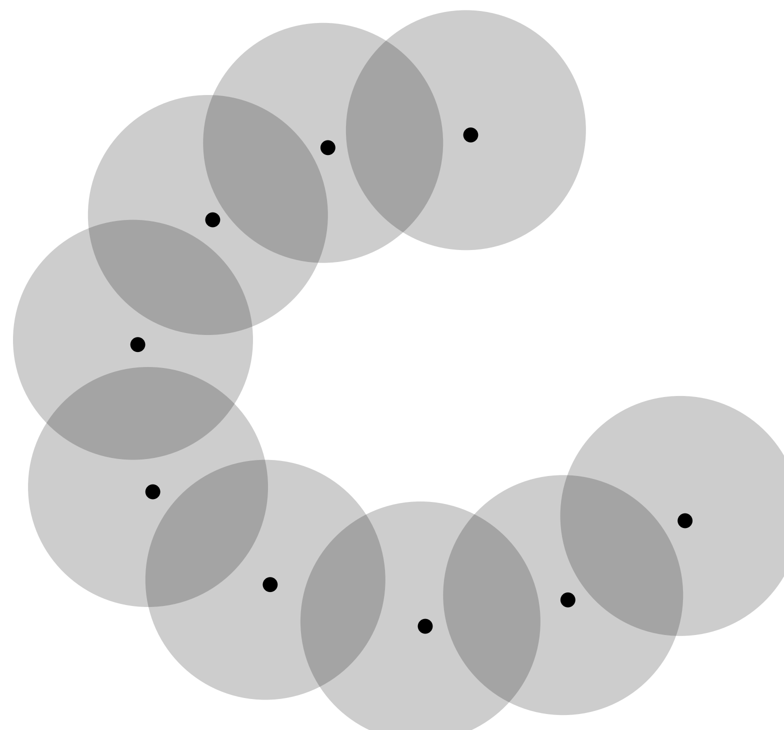
- Used for photographic object recognition
- Detected parts arranged in approximate spatial configuration
- Successful fit identifies required parts near expected position

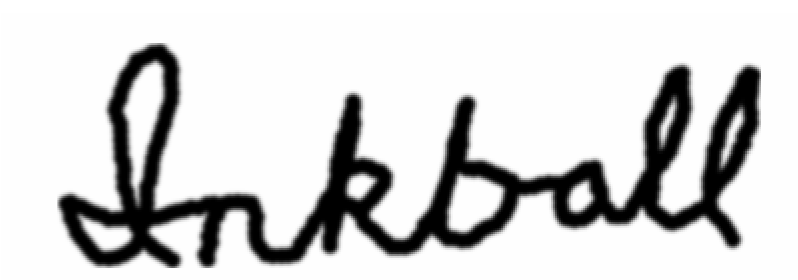
Inkball Models

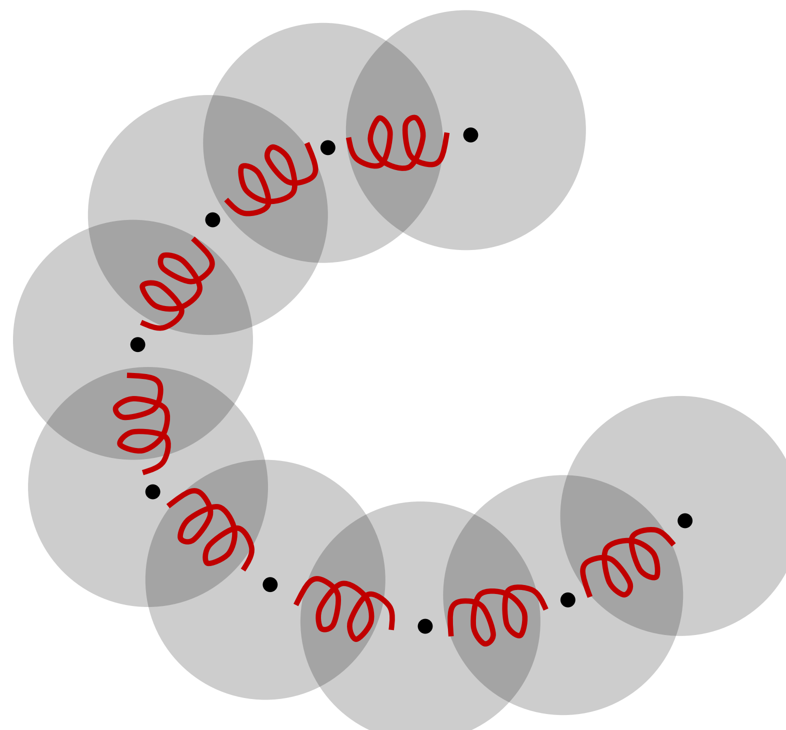
- Model = Closely spaced inkballs forming curve
- Part = Ball of ink
- Tree structure



Inkball Models

- Model = Closely spaced inkballs forming curve
- Part = Ball of ink
- Tree structure
- Connections are flexible links





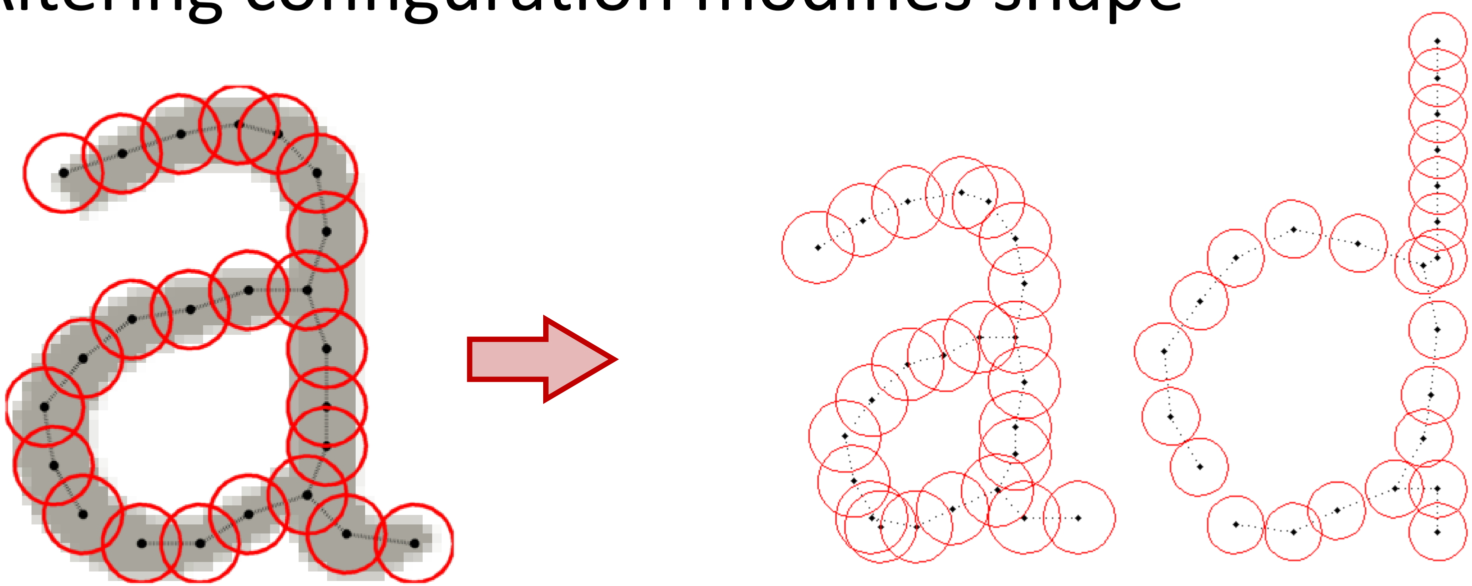
Part-Structured Inkball Models for One-Shot Handwritten Word Spotting

So, now you know.

…but how do we use these models for word spotting?

Configurations

- Configuration = 2D position for each ball
- Rest/default configuration derived from example
- Altering configuration modifies shape



Rest Configuration

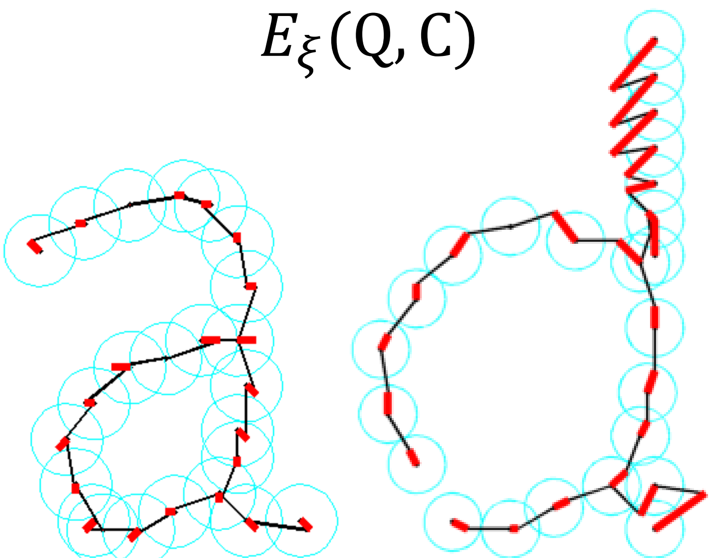
Alternate Configurations

Configuration Energy

- Match of model to image has two terms:

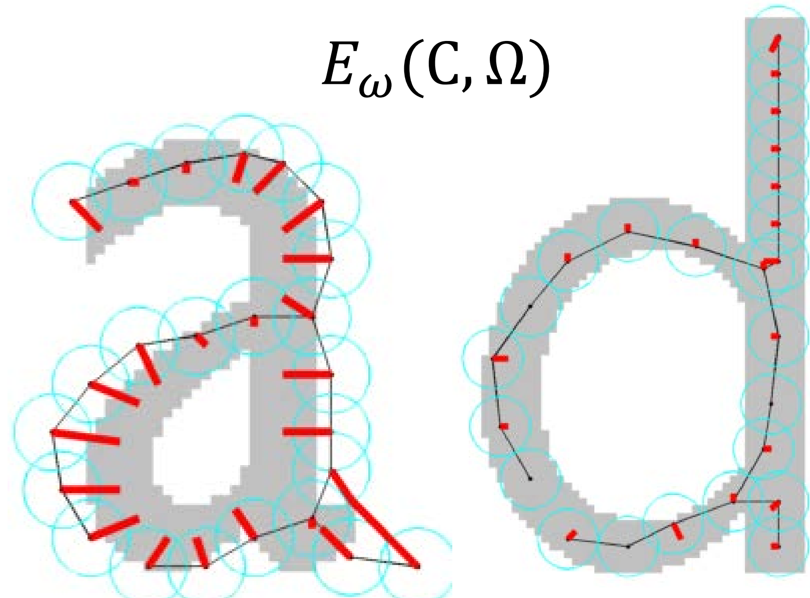
Internal deformation:
how far from default?

$E_{\xi}(\mathrm{Q}, \mathrm{C})$



Observational deformation:
how far from ink skeleton?

$E_{\omega}(\mathrm{C}, \Omega)$



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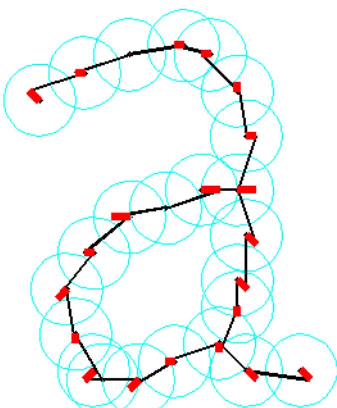
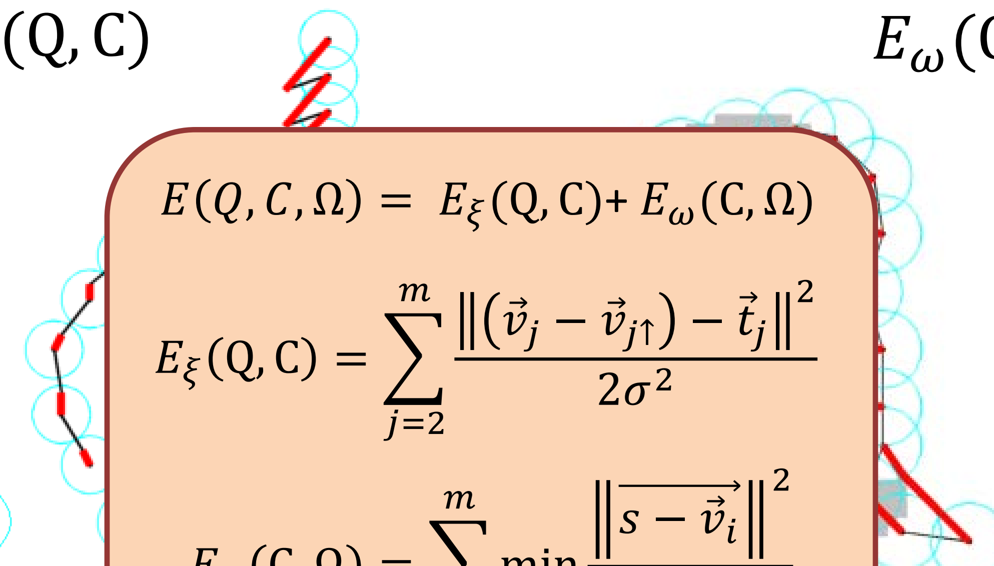
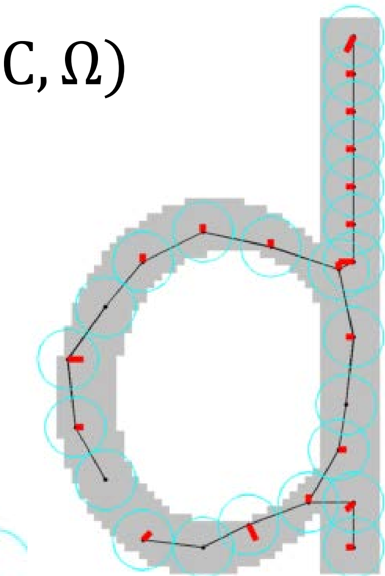




$$E(Q,C,\Omega) = E_{\xi}(\mathrm{Q},\mathrm{C}) + E_{\omega}(\mathrm{C},\Omega)$$

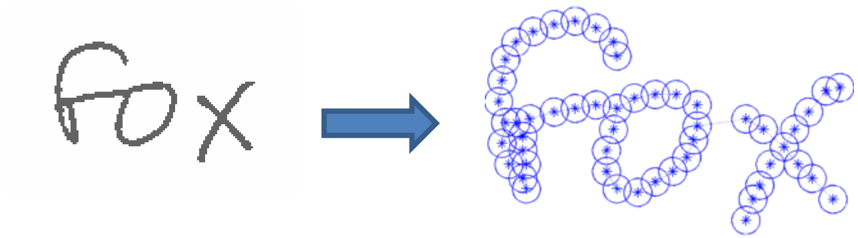
$$E_{\xi}(\mathrm{Q},\mathrm{C}) = \sum_{j=2}^{m} \frac{\left\| \left(\vec{v}_j - \vec{v}_{j\uparrow}\right) - \vec{t}_j \right\|^2}{2\sigma^2}$$

$$E_{\omega}(\mathrm{C},\Omega) = \sum_{i=1}^{m} \min_{\vec{s}\in S} \frac{\left\| \overrightarrow{s - \vec{v}_i} \right\|^2}{2\acute{\sigma}_i{}^2}$$

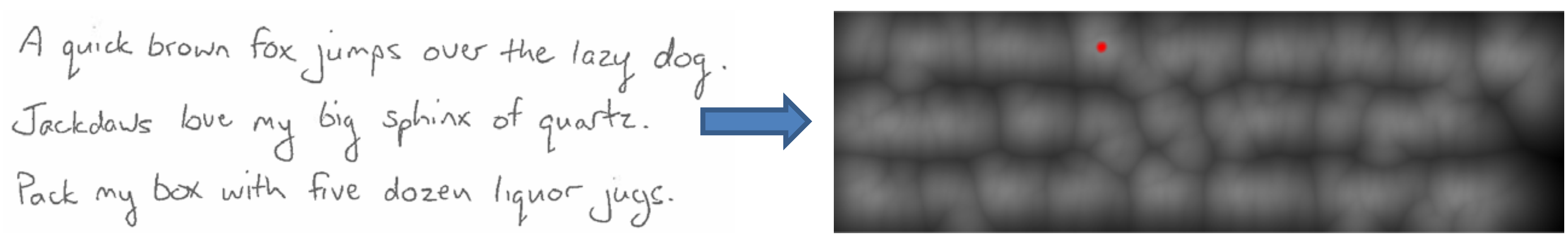


One-Shot Word Spotting

1. Infer inkball model from word sample

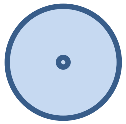


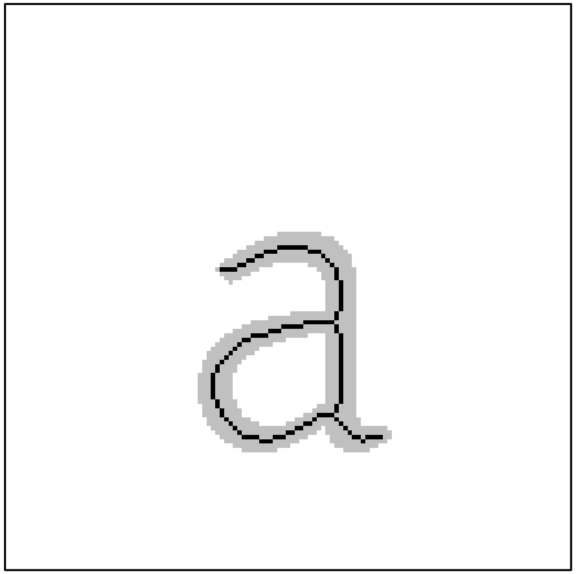
2. Efficiently identify model configurations with low energy in target document



3. Confirm candidates via reverse match

Efficient Energy Minimization

- Consider simplest case: single-node model 
  - Observation deformation is only term in play
  - Compute the energy for all possible configurations
    Distance to closest ink is just a distance transform



Target image

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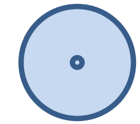

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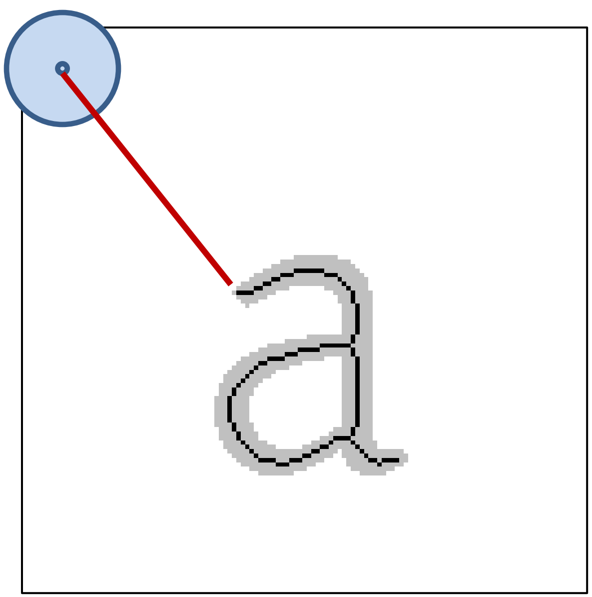

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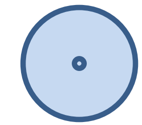
- Consider simplest case: single-node model 
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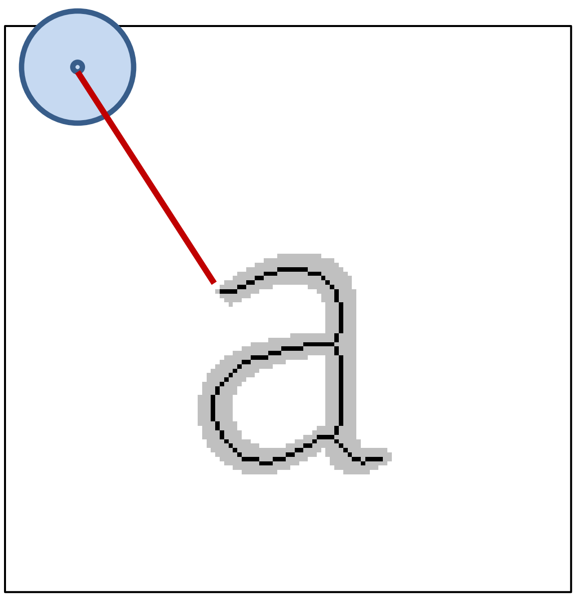

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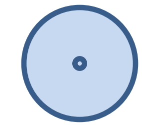
- Consider simplest case: single-node model 
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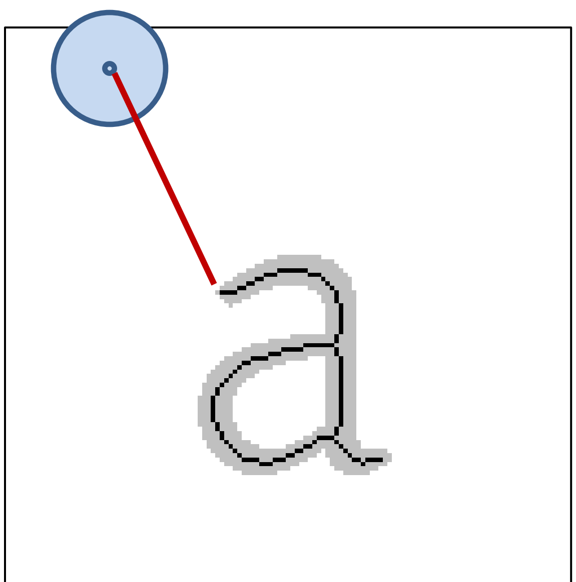

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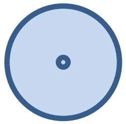

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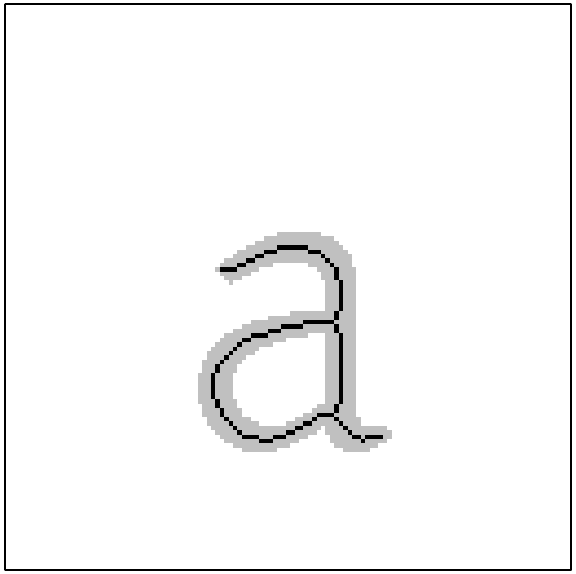

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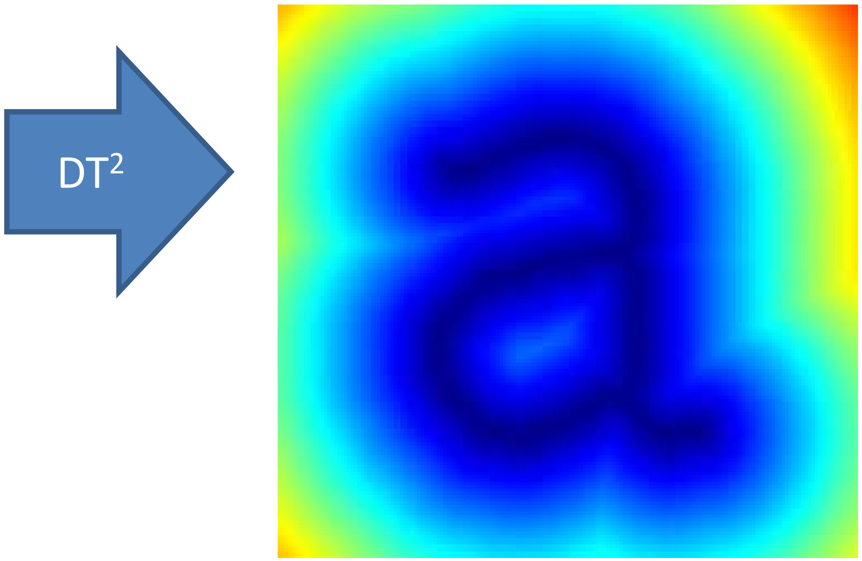

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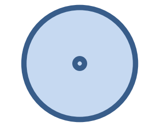
- Consider simplest case: single-node model 
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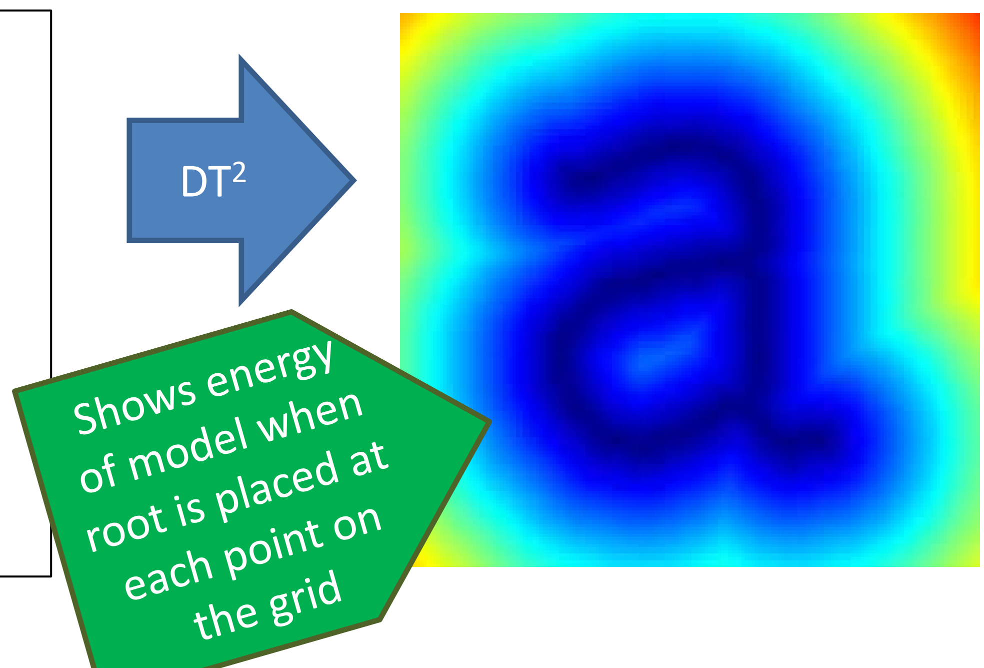

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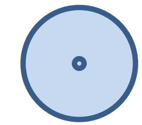
- Consider simplest case: single-node model 
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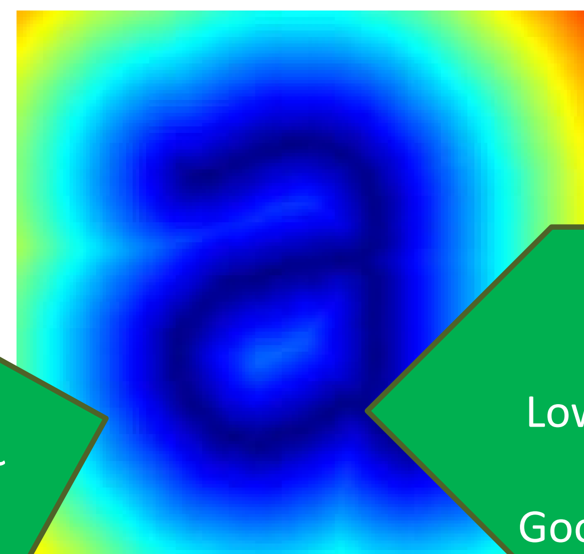
Target image

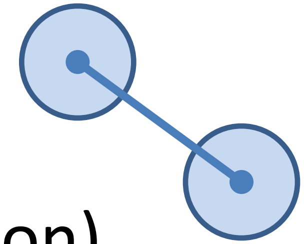
DT²



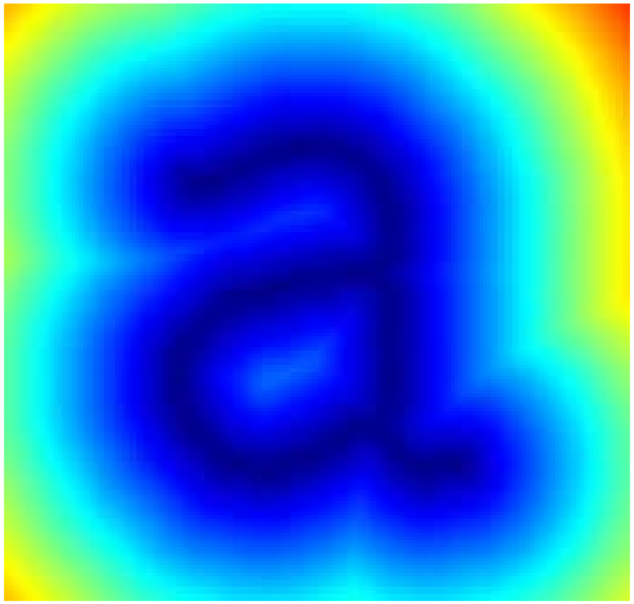
Shows energy of model when root is placed at each point on the grid

Blue == Low energy == Good match

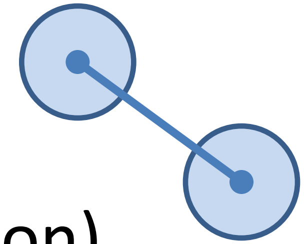
Efficient Energy Minimization



- Slightly harder case: **barbell model**
  - Still observation terms only (fixed separation)
  - Energy is sum of offset distance transforms:



Efficient Energy Minimization



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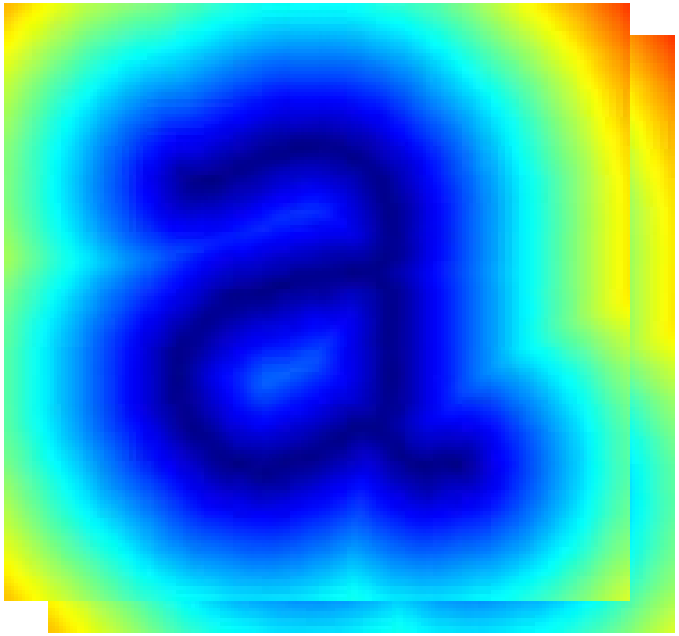

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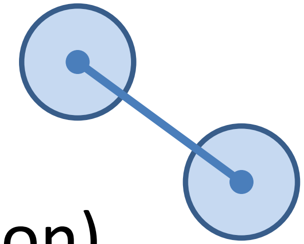

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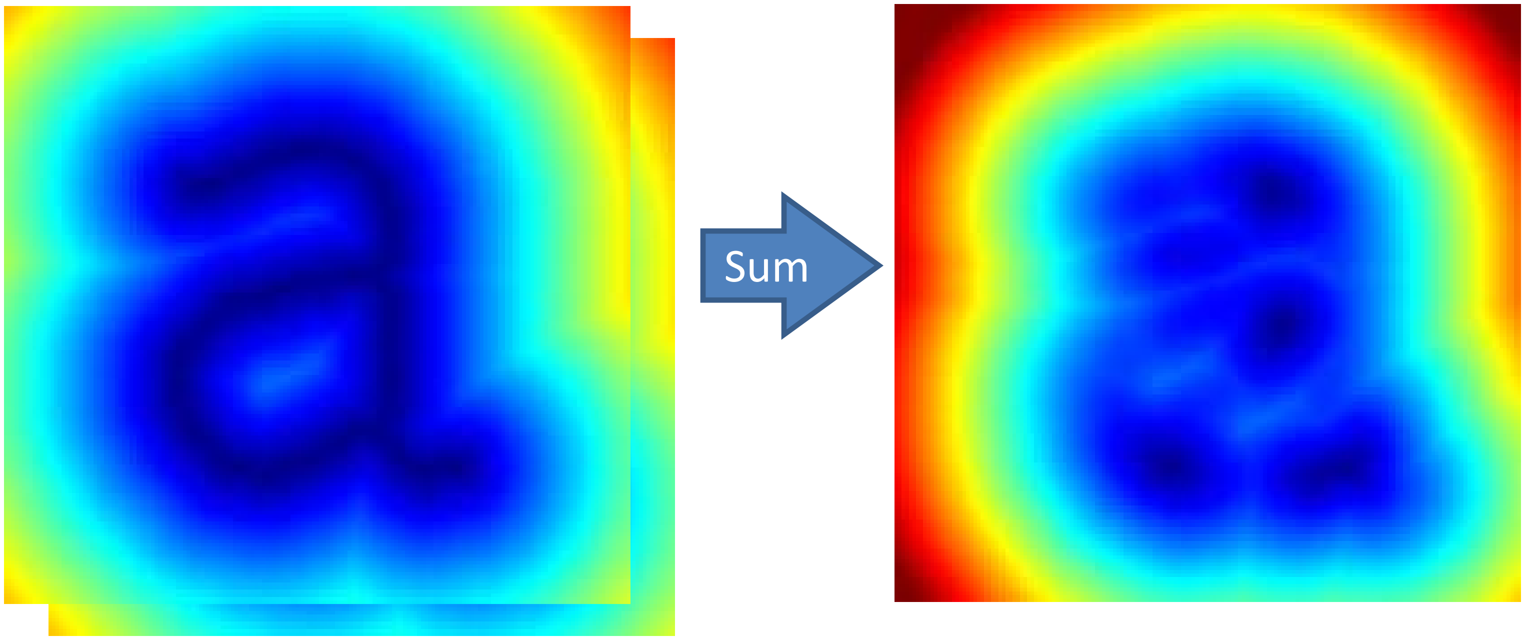

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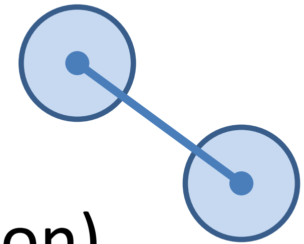

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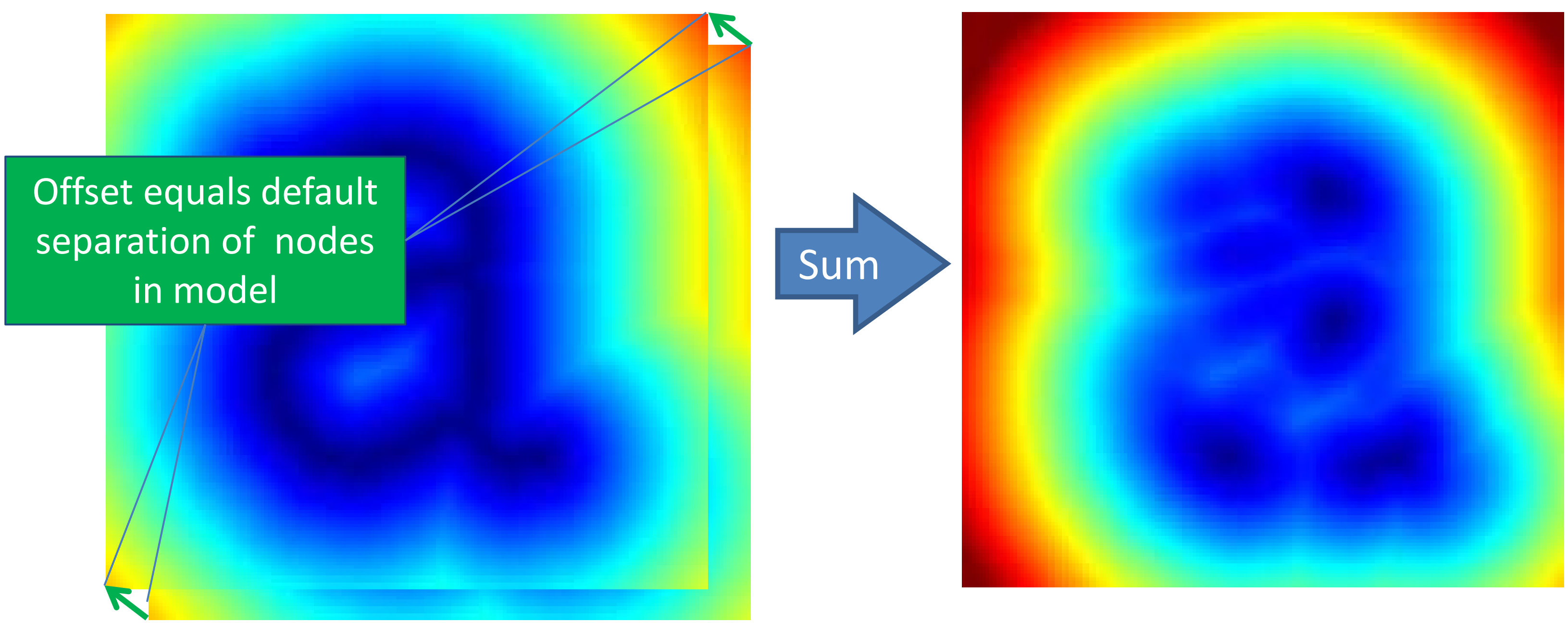

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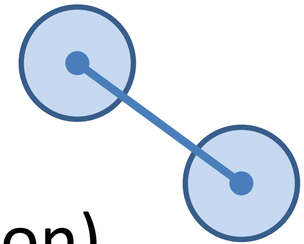

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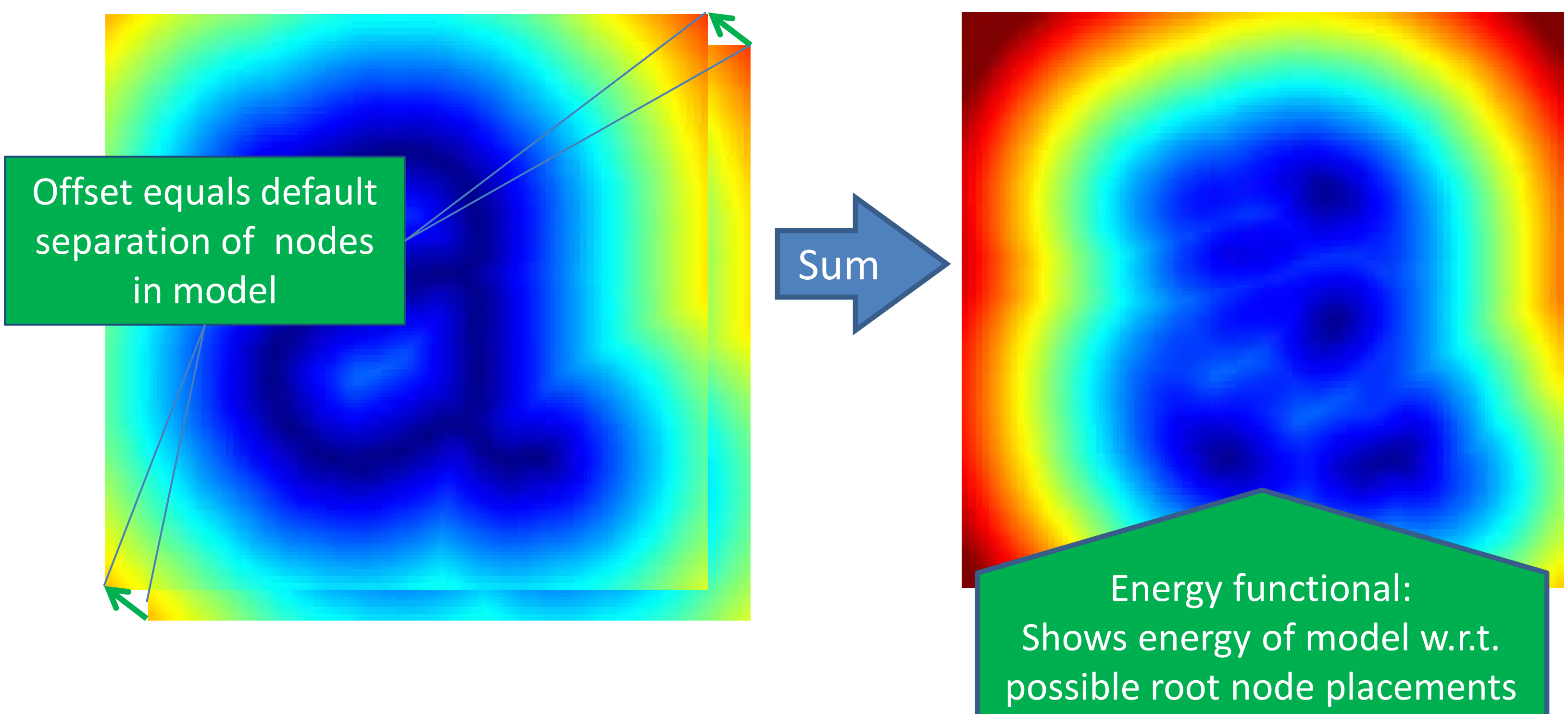
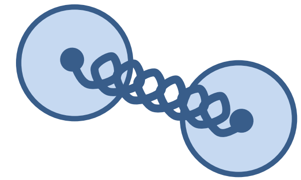
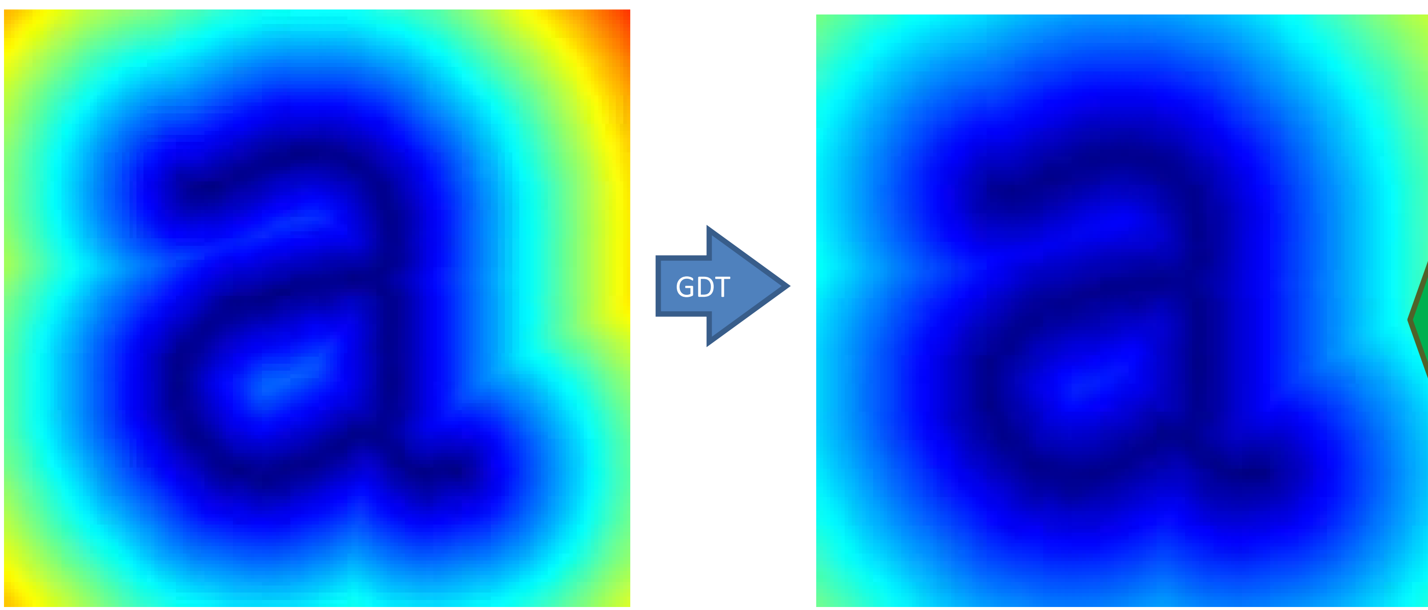


Efficient Energy Minimization



- More complication: springy barbell
  - Internal deformation term enters picture
  - Use *generalized distance transform* on offset energy

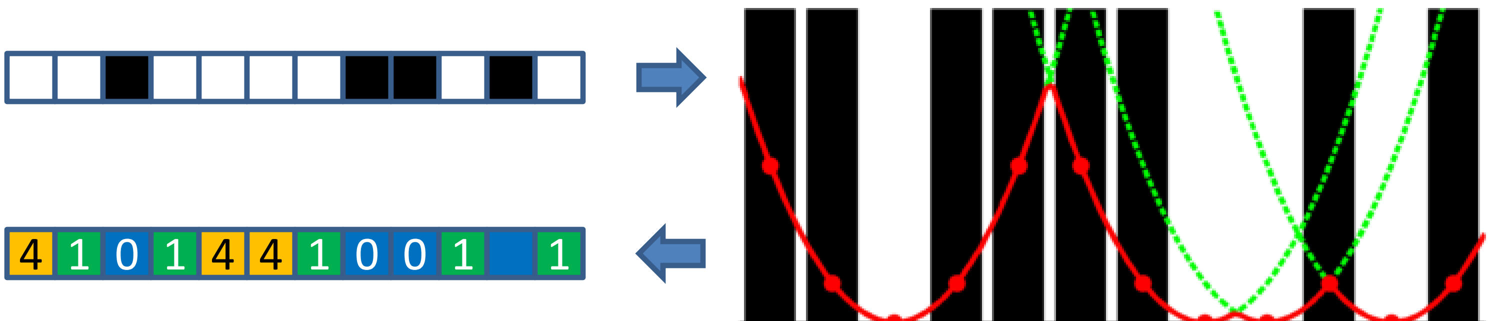


Energy on grid points with optimal observation / deformation tradeoff

(Squared) Distance Transform

- Minimum of upward paraboloids extending from ink pixels only, rooted at zero

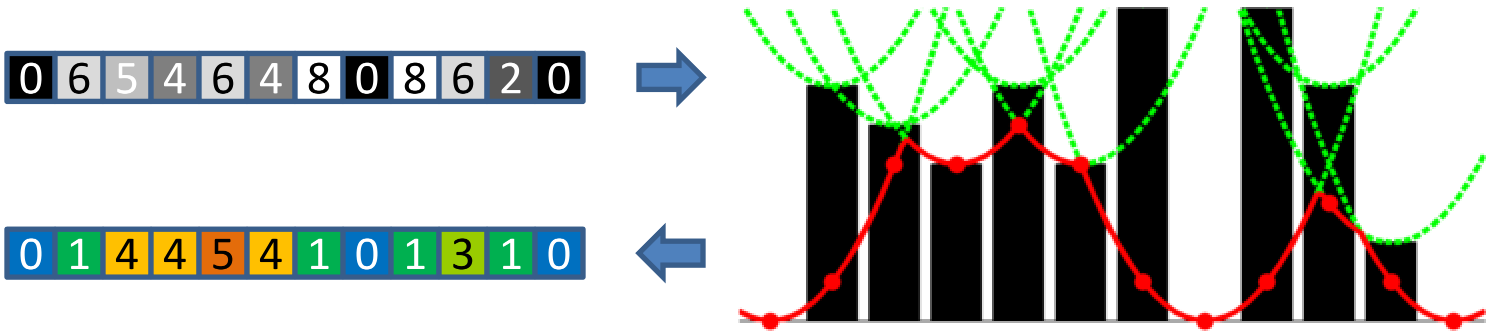
1D Example:



Note: Computational complexity grows linearly with number of pixels

Generalized Distance Transform

- Minimum of upward paraboloids *at every pixel* but rooted at pixel value
  - *Still linear complexity in number of pixels*

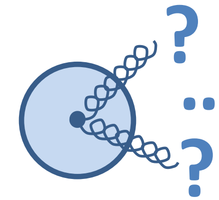


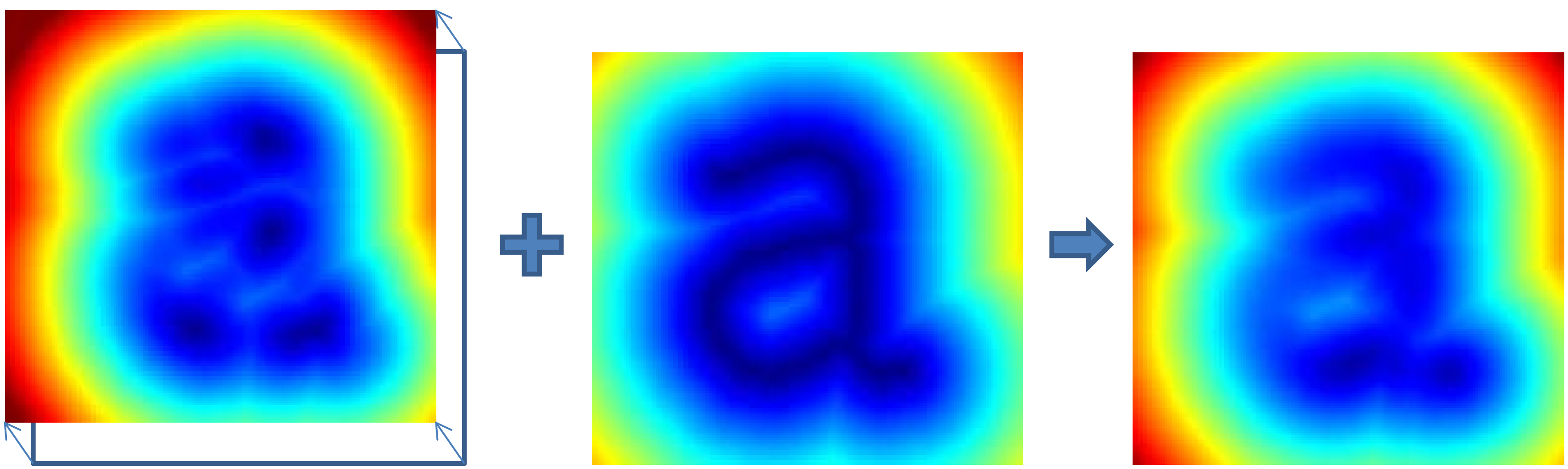
- Intuition:

  The local value can be beaten by a better one nearby

Efficient Energy Minimization

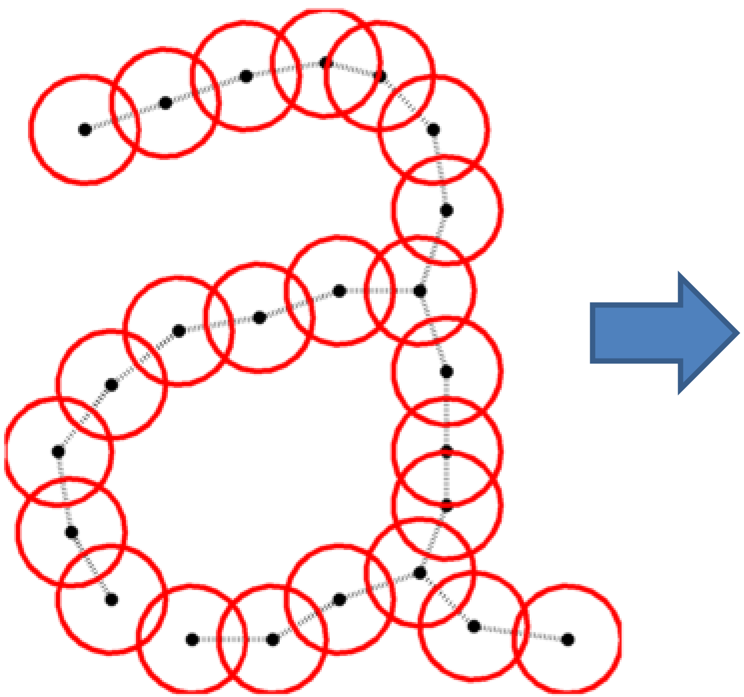
- General case: node + arbitrary structure
  - Translate energy of child structure(s) by offset
  - Apply generalized distance transform
  - Add to single-node energy

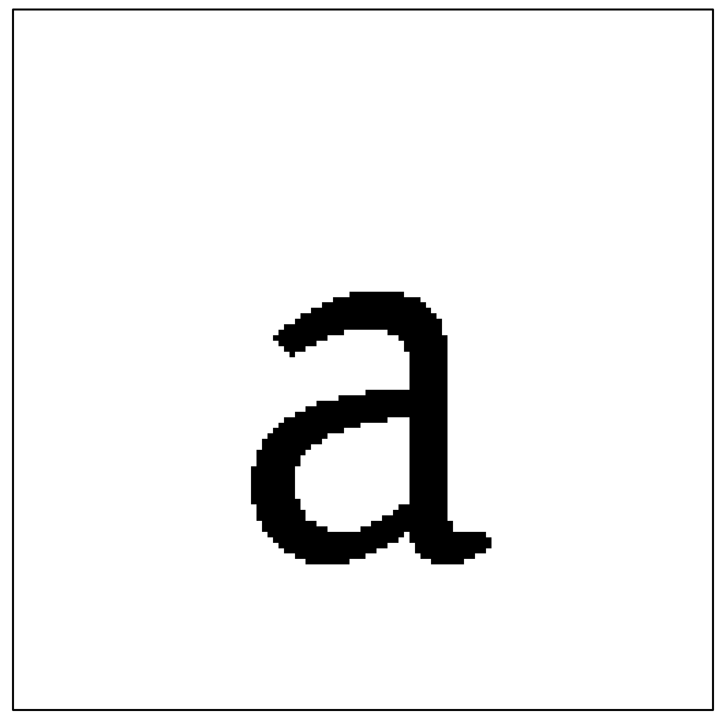




Model Matching Visualization

- Demonstration with simple example:
  Match model **a** to image





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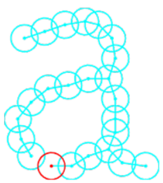
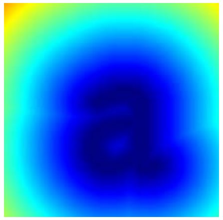


Single Node



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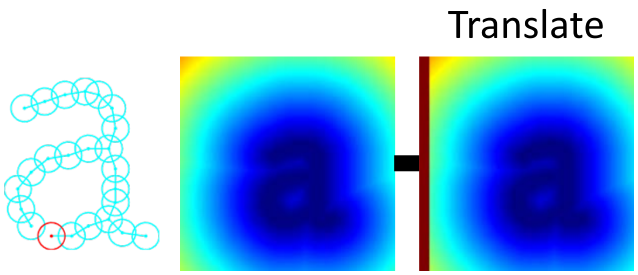

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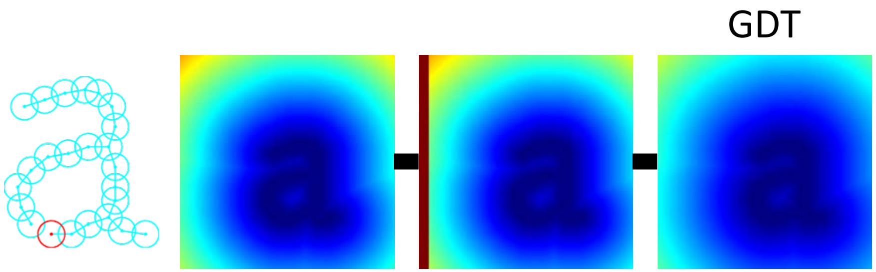

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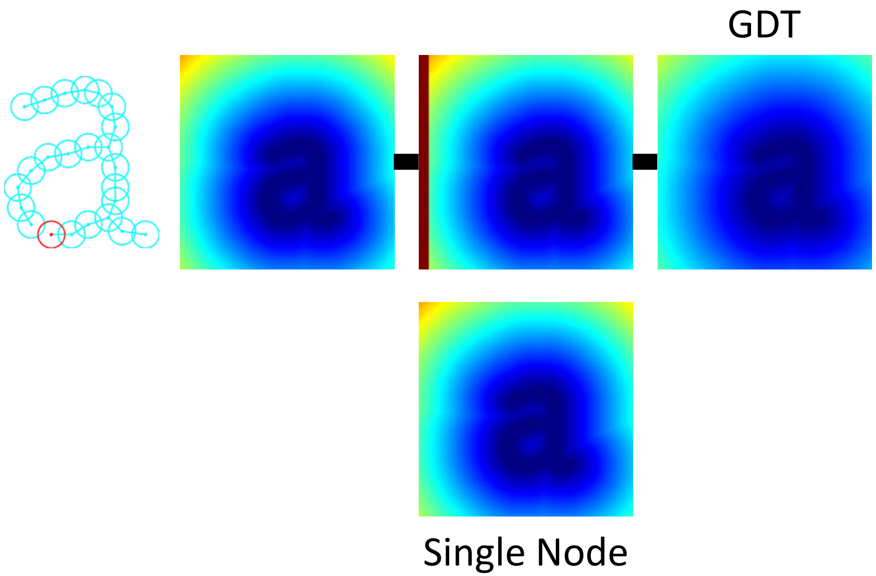

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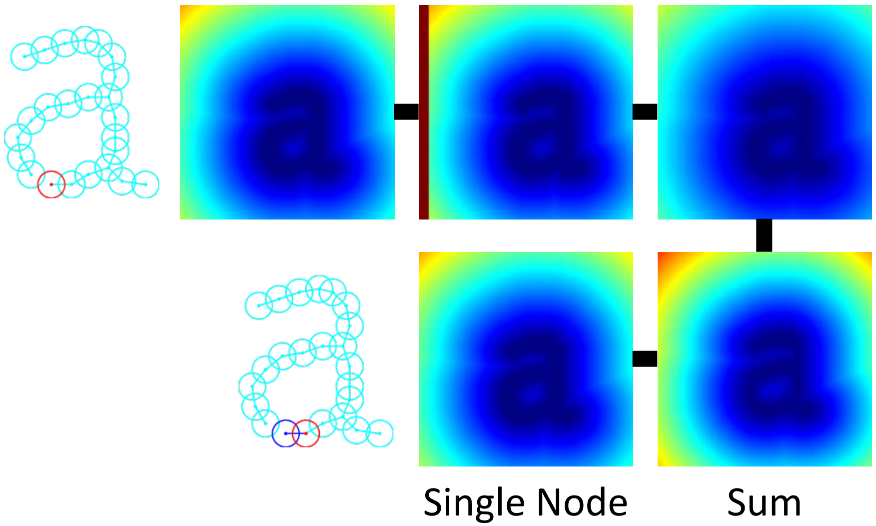

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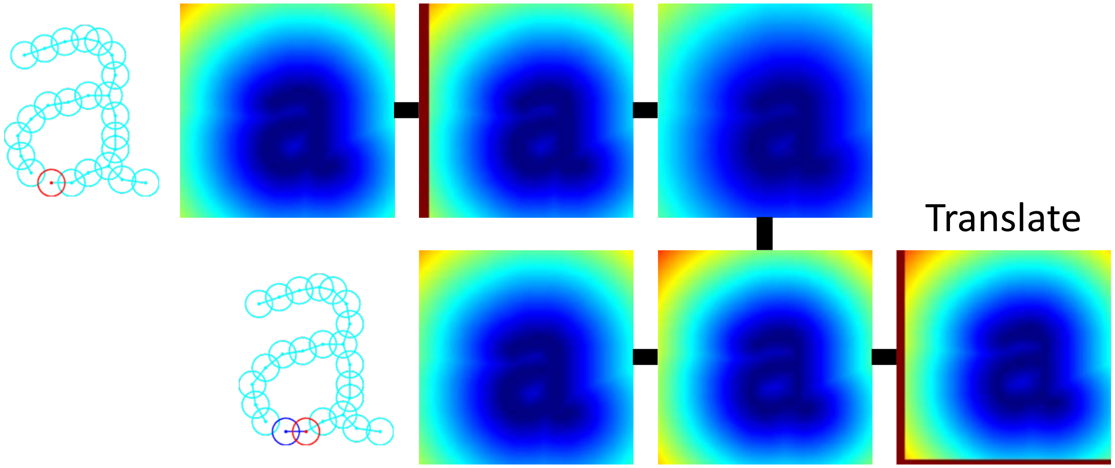

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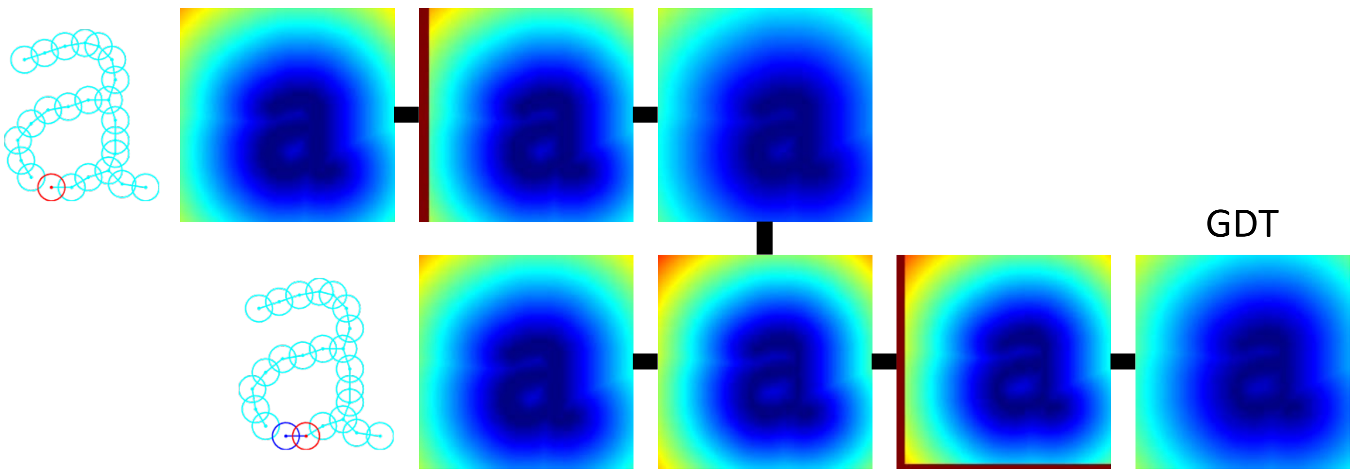
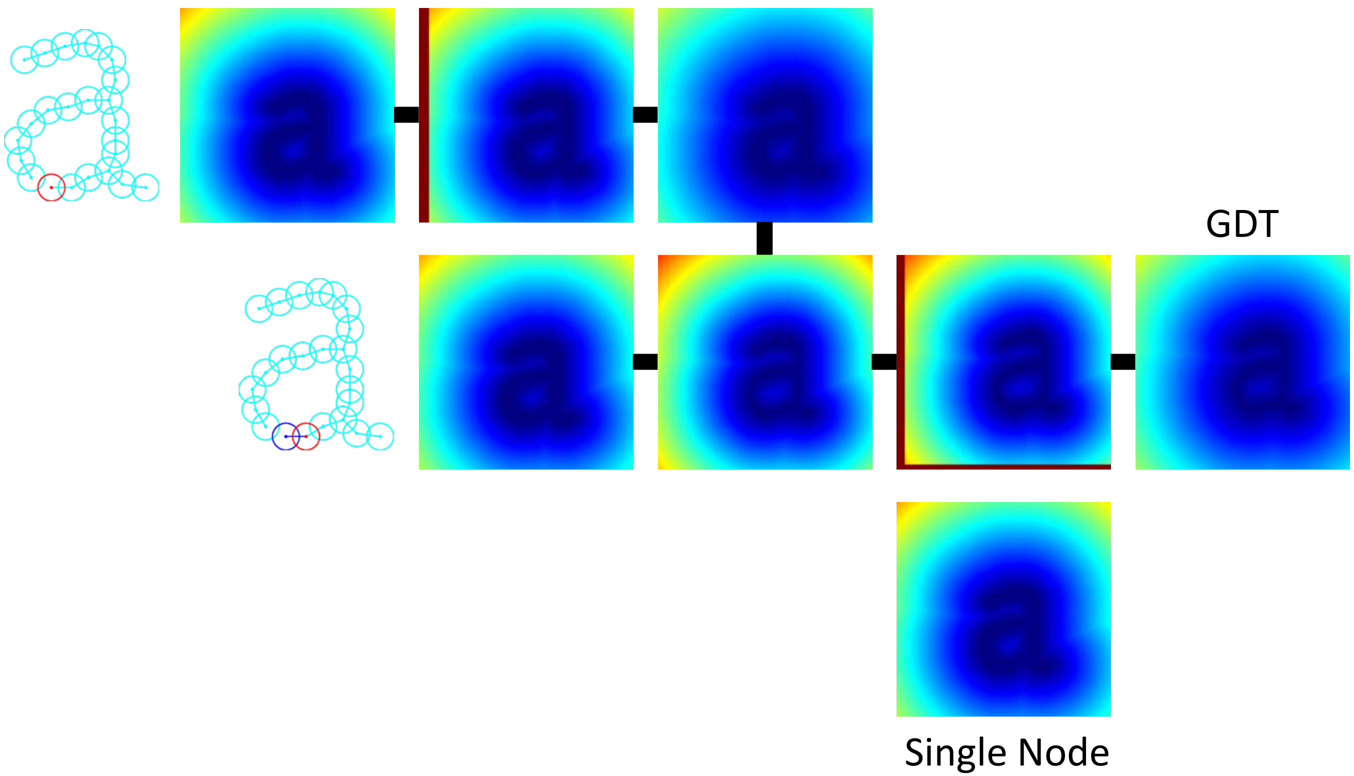
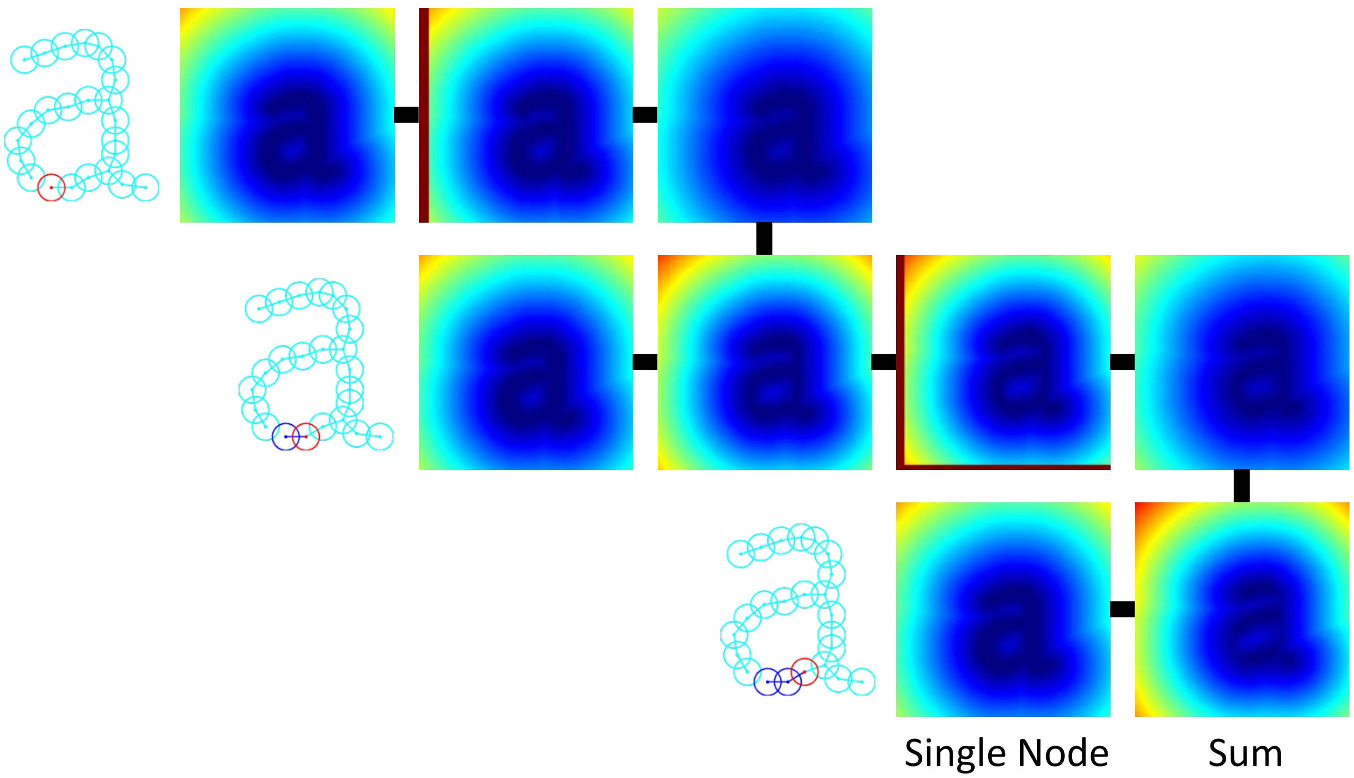


Model Matching Visualization

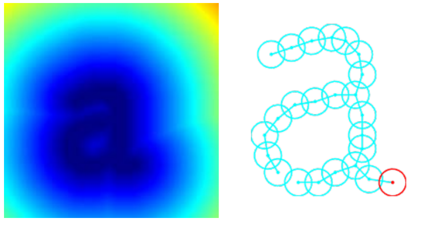


Model Matching Visualization



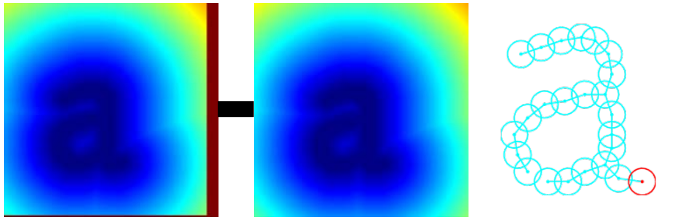
Model Matching Visualization

Single Node



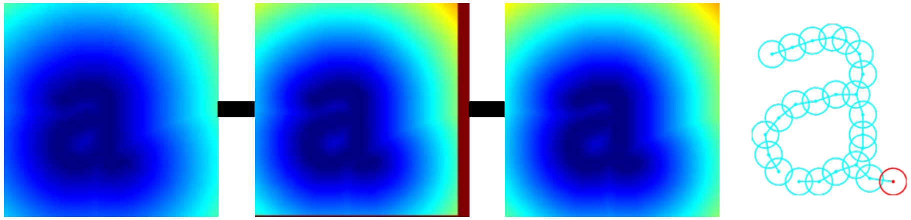
Model Matching Visualization

Translate

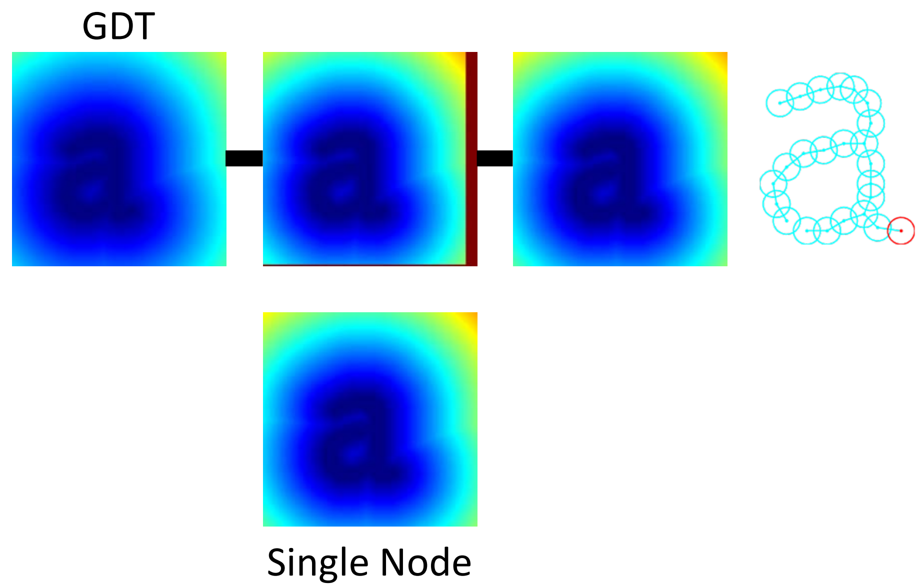


Model Matching Visualization

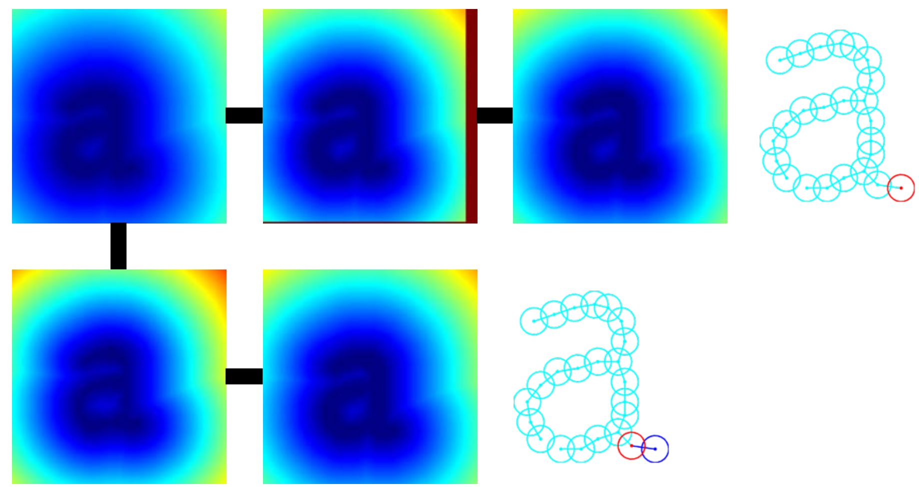
GDT



Model Matching Visualization



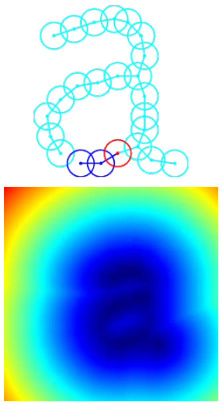
Model Matching Visualization

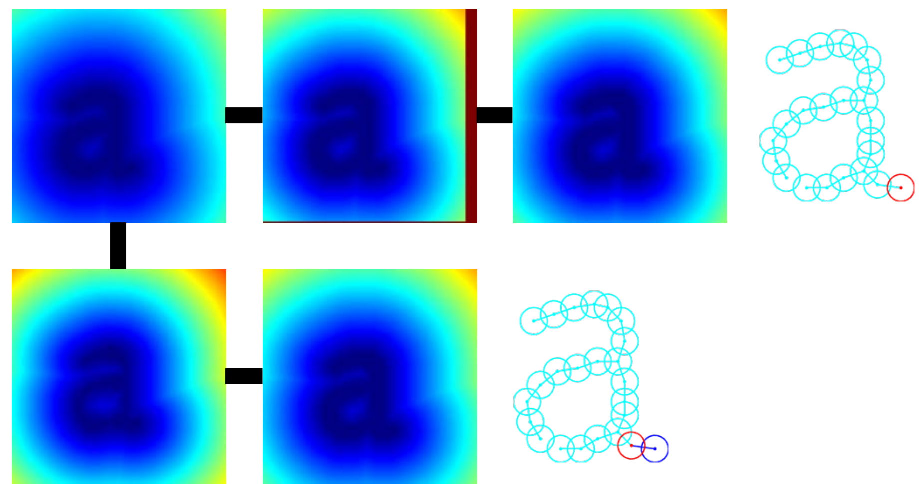


Sum

Model Matching Visualization

Subtree





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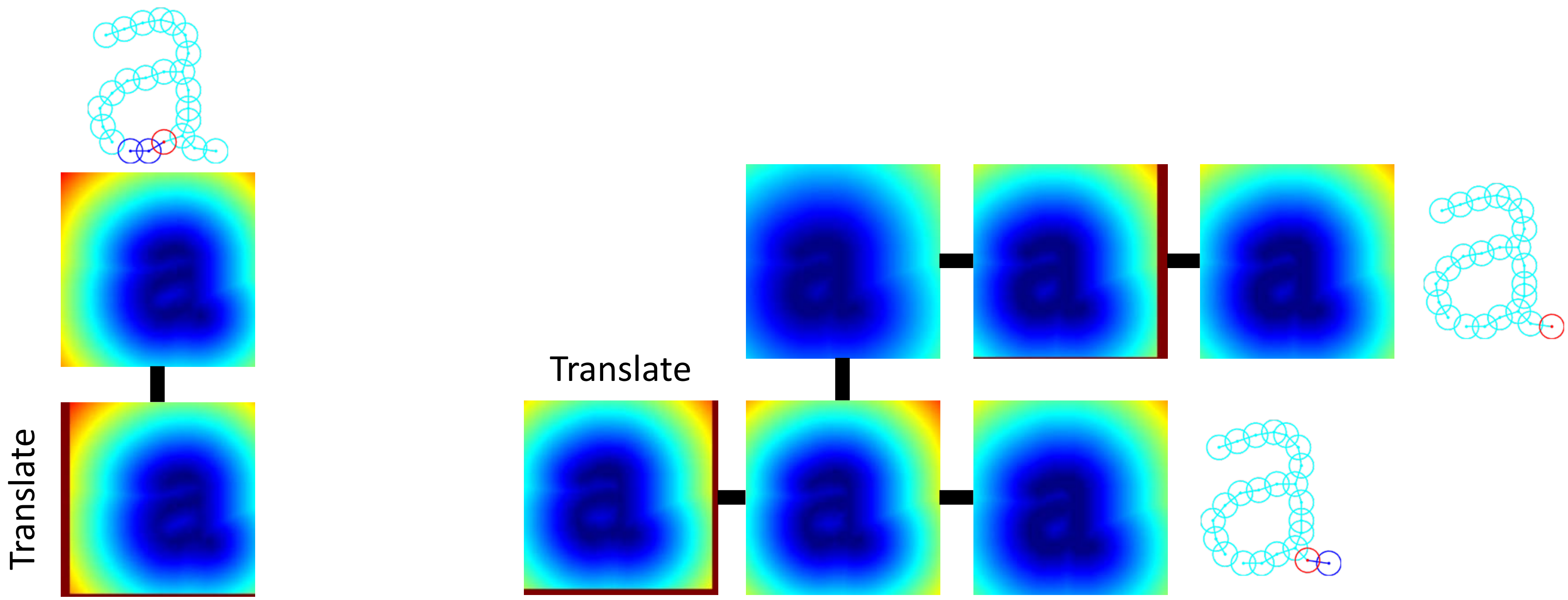
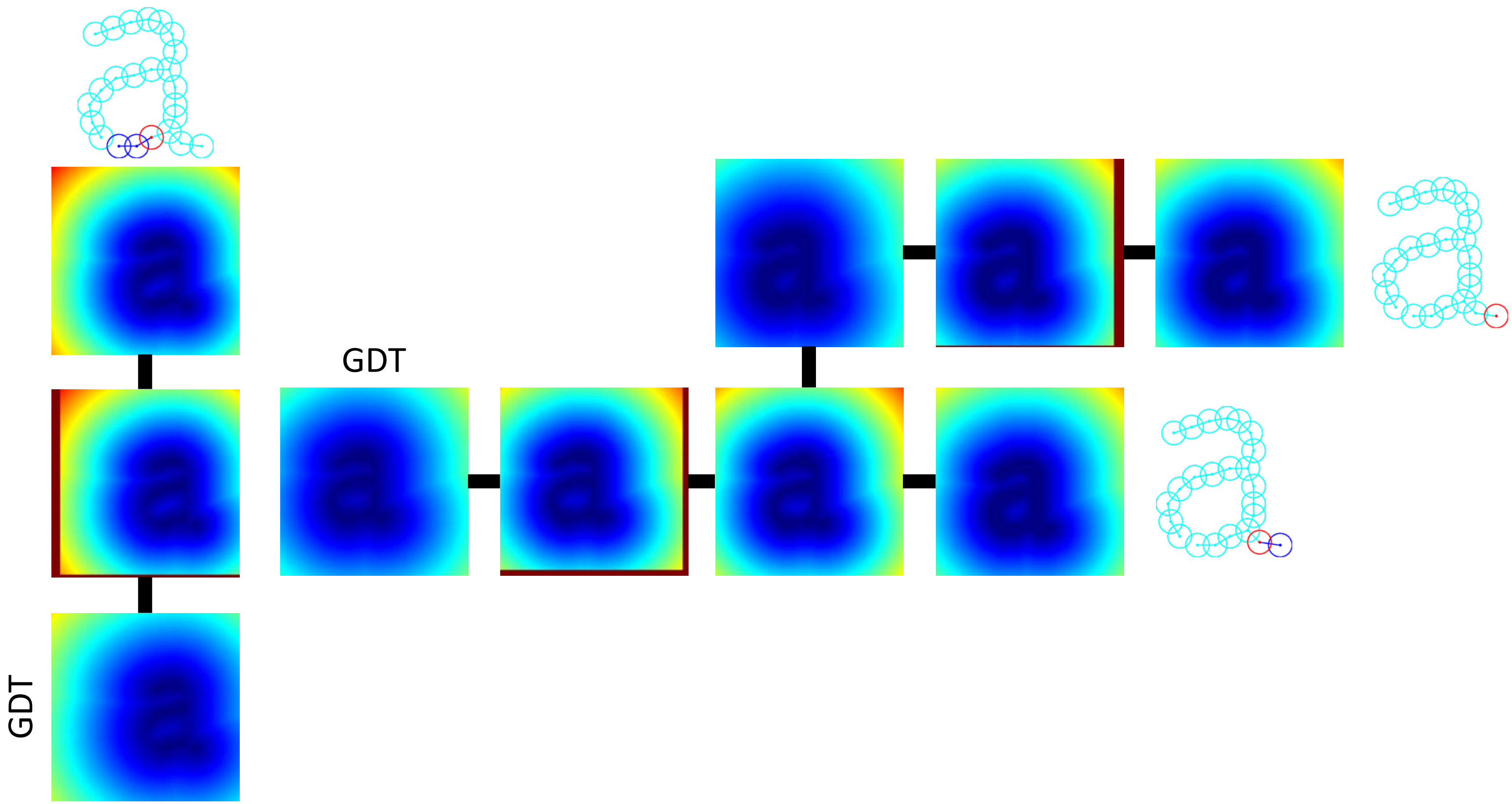
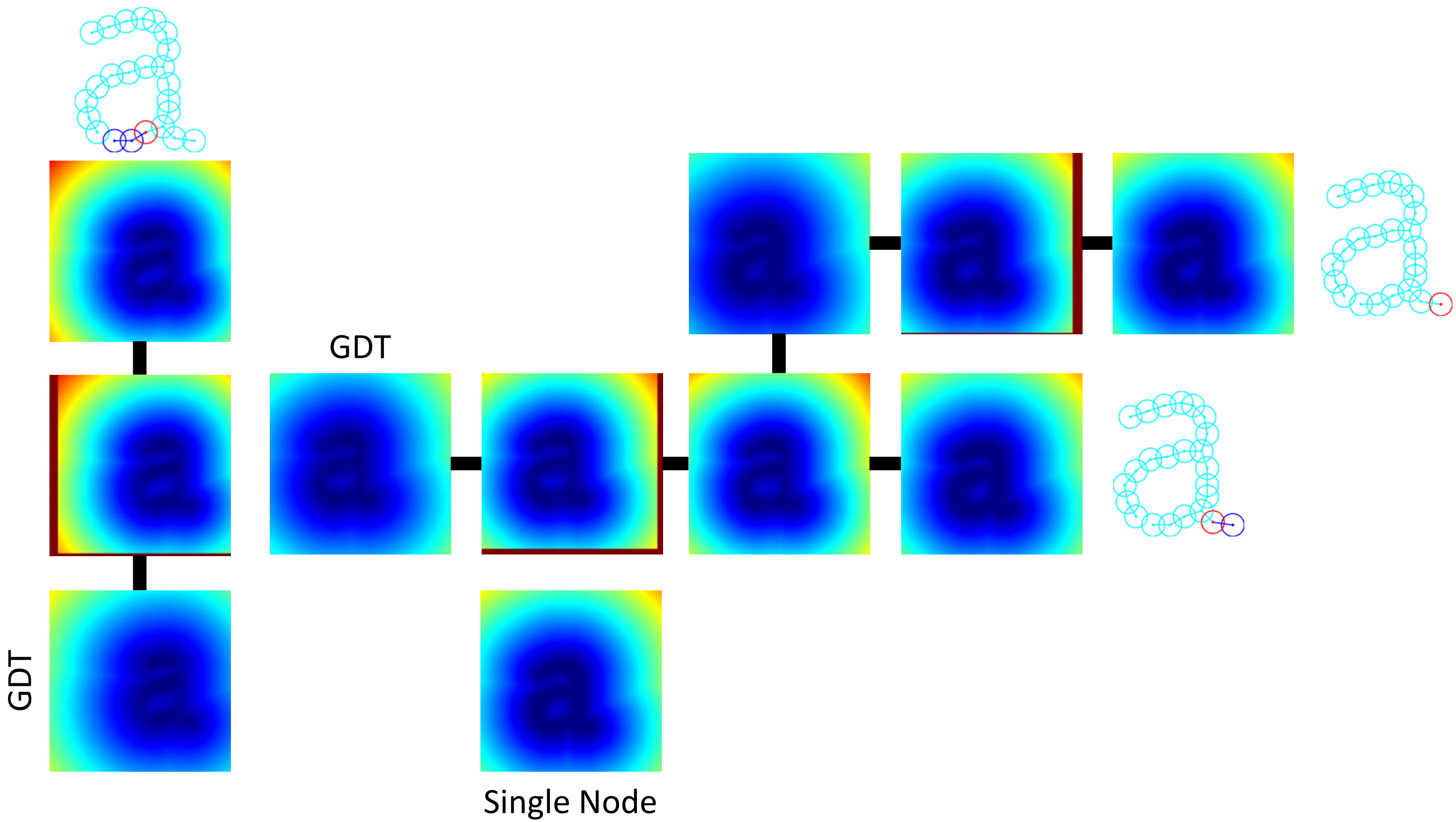


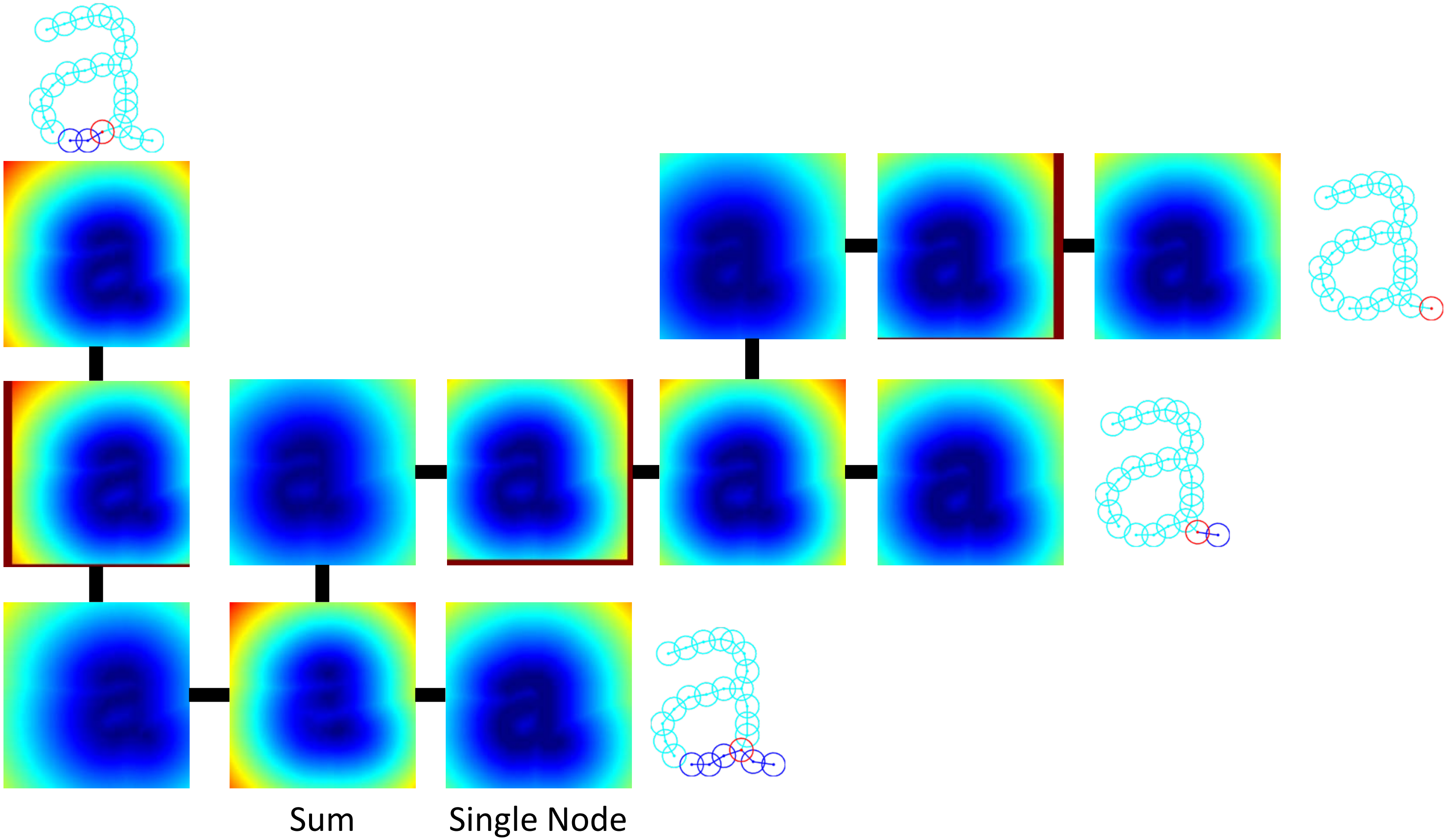
Model Matching Visualization



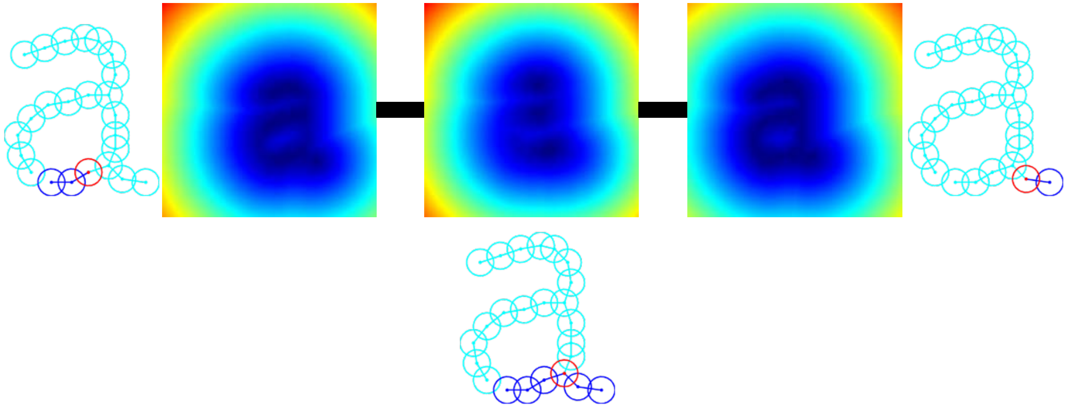
Model Matching Visualization



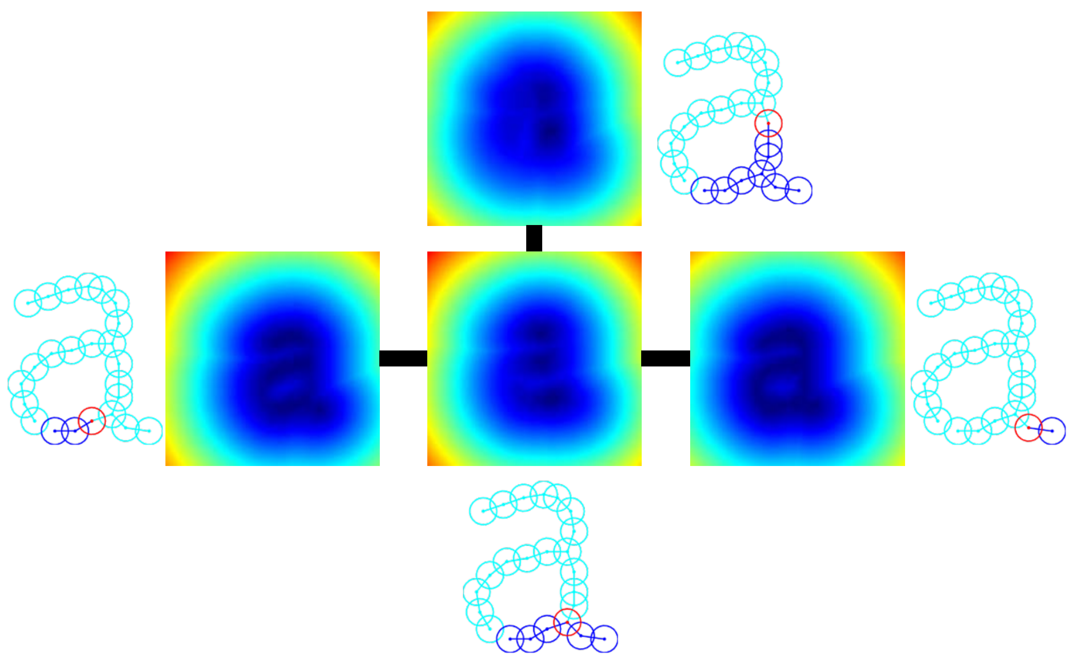
Model Matching Visualization



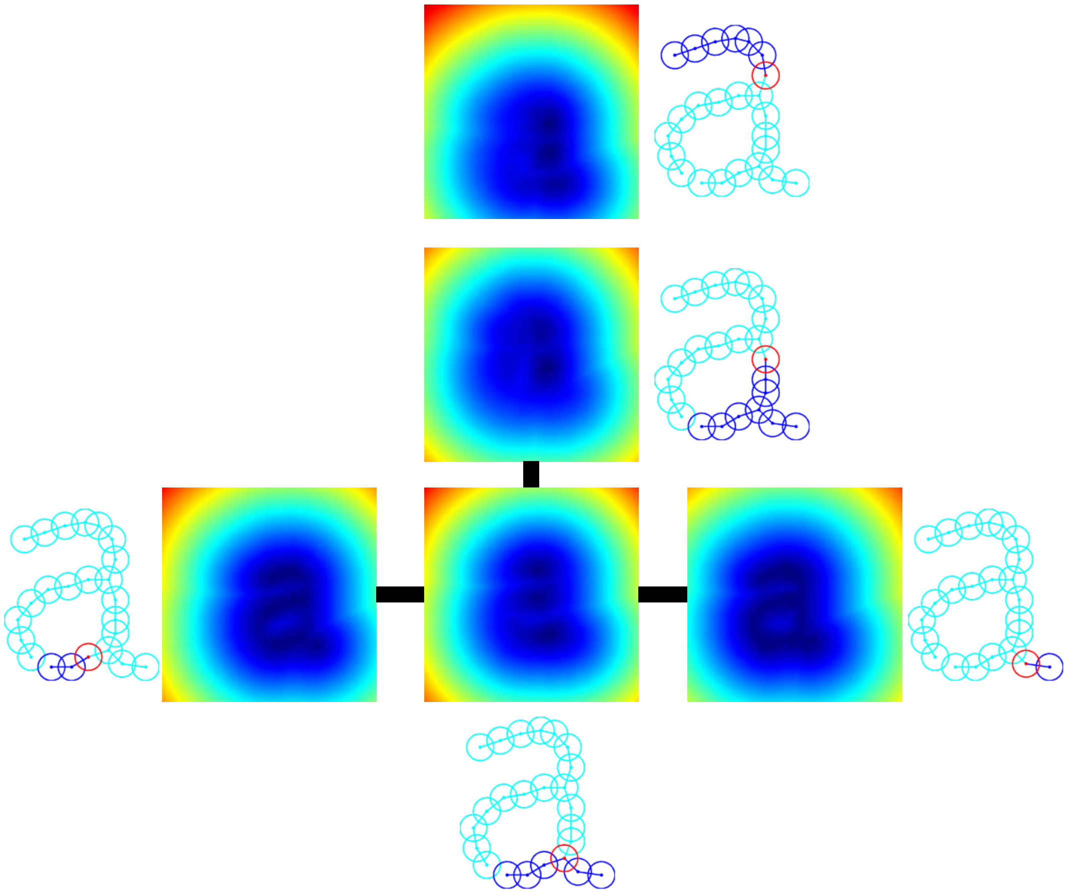
Model Matching Visualization



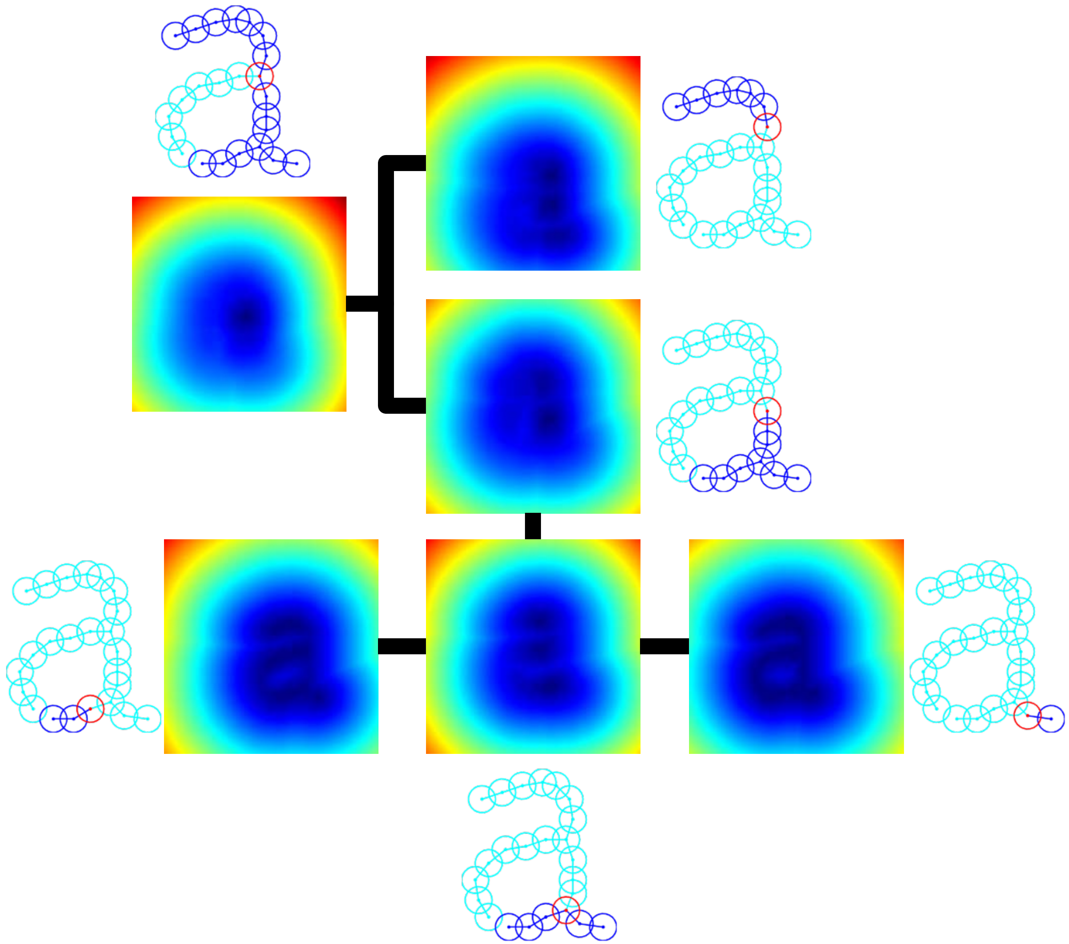
Model Matching Visualization



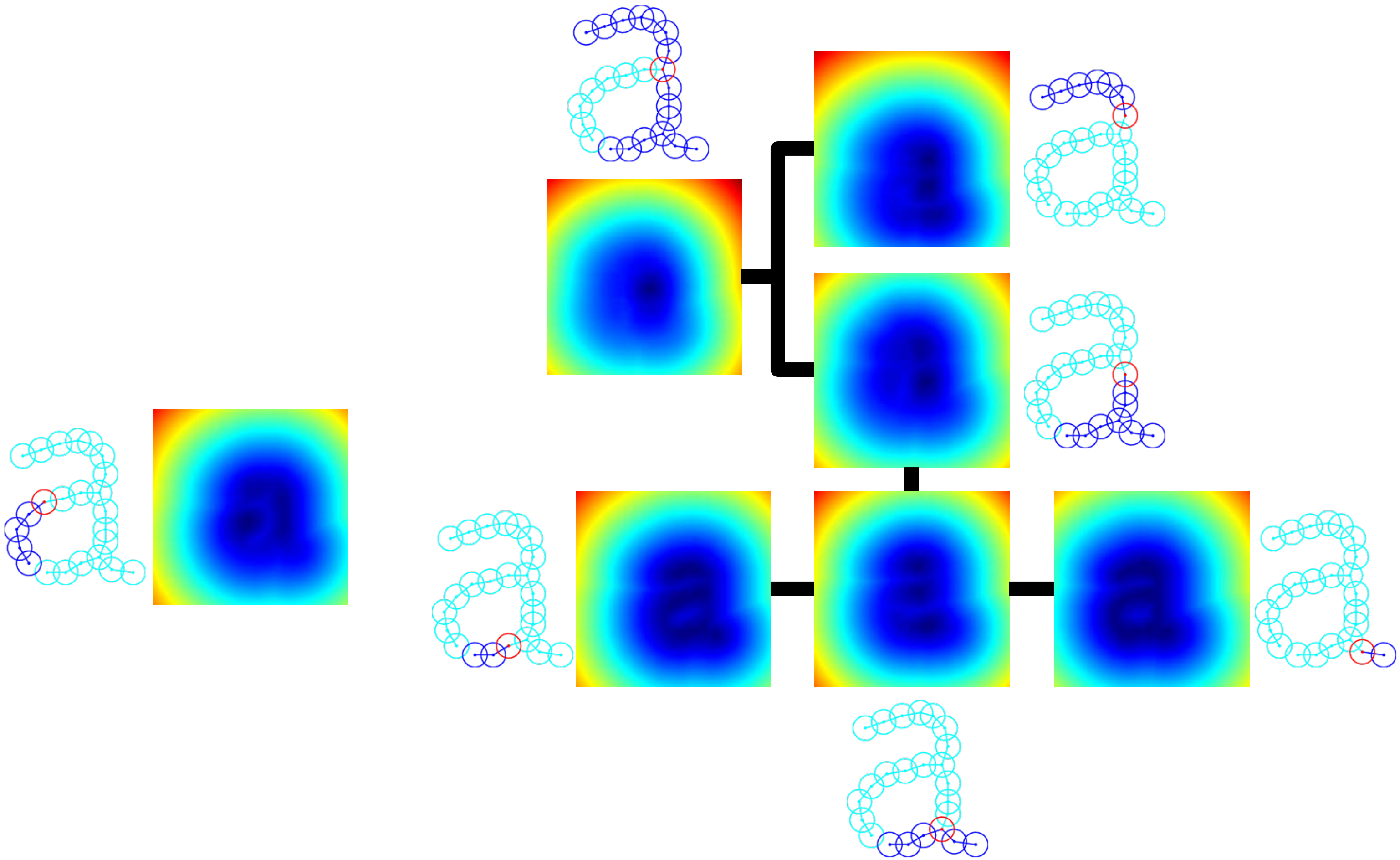
Model Matching Visualization



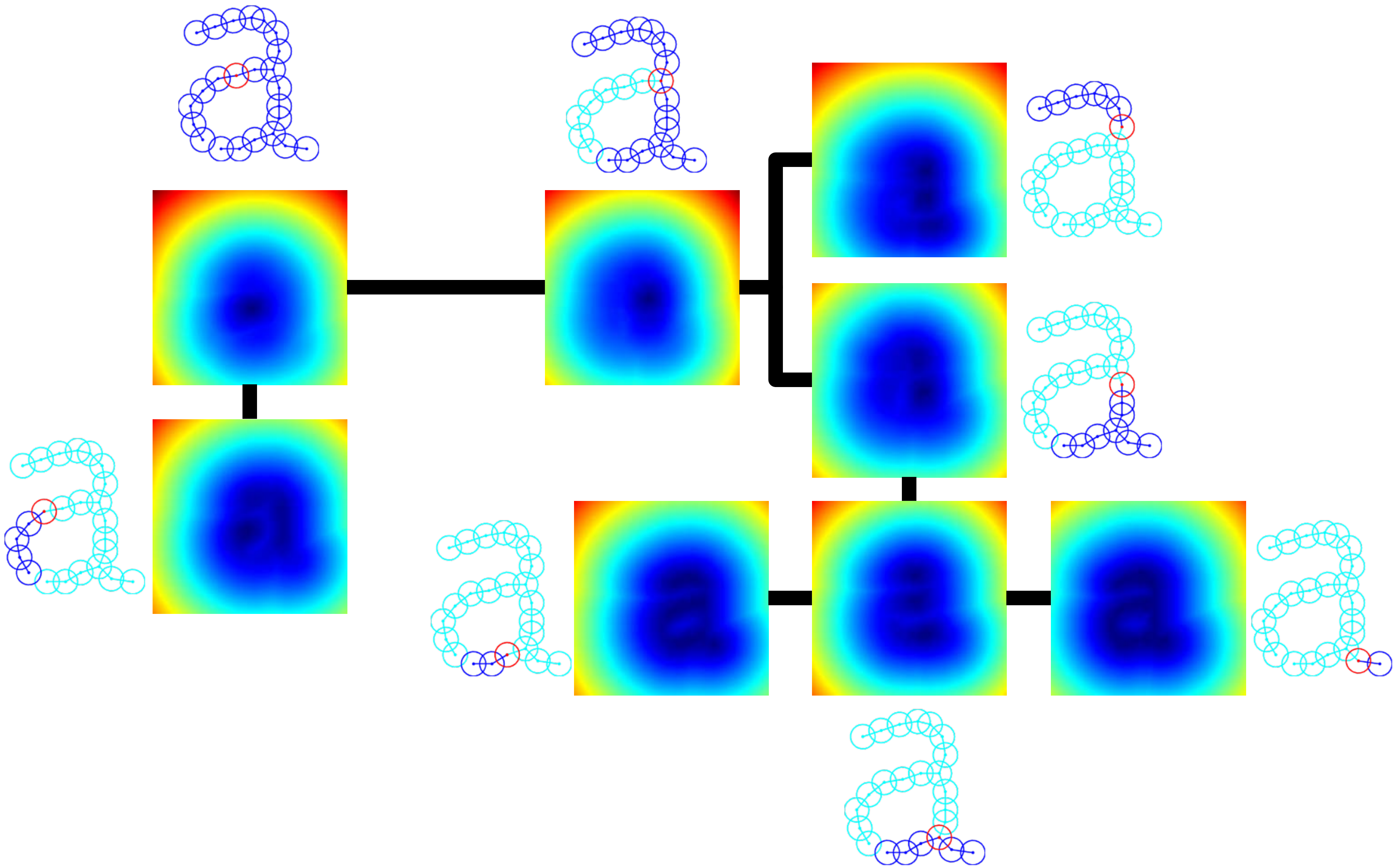
Model Matching Visualization



Model Matching Visualization

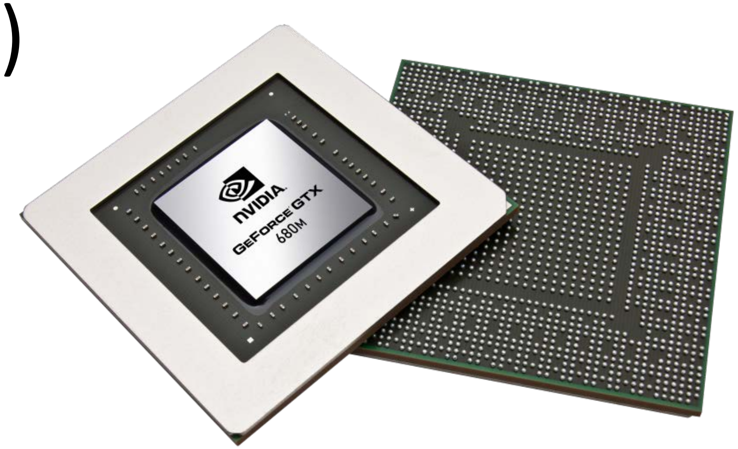


Model Matching Visualization



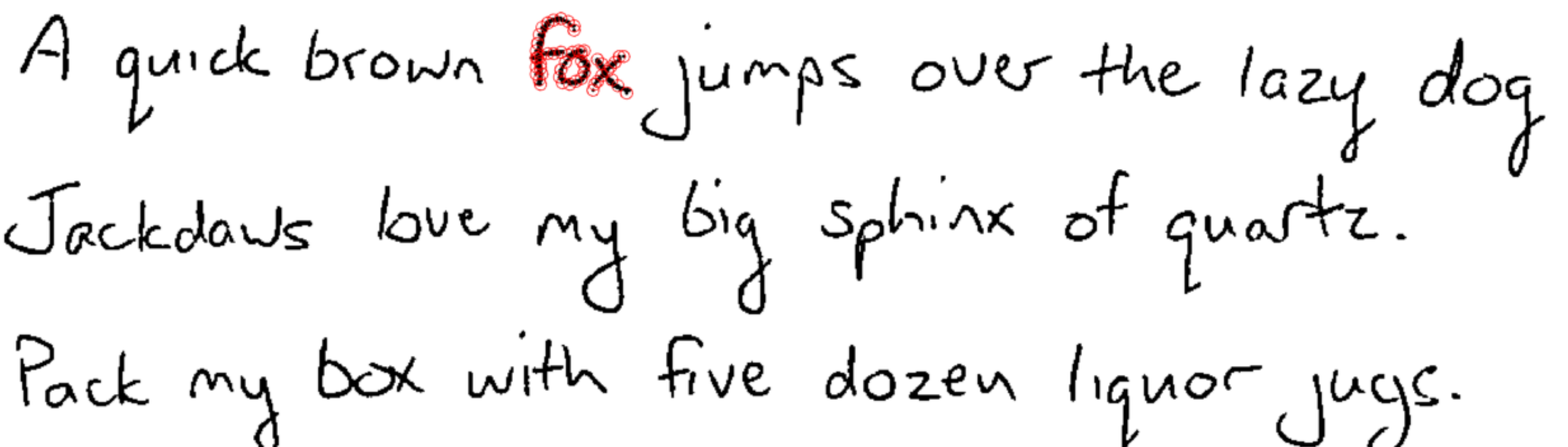
Parallel GDT

- Optimum model fit requires:
  - One translation per node
  - One GDT per node
- Work scales with number of image pixels
- Fast parallel computation on graphics processing unit (GPU)



Configuration Recovery

- Energy optimization/model matching is just big dynamic programming problem
- Trace back DP winner to recover configuration
- Useful for display/localization



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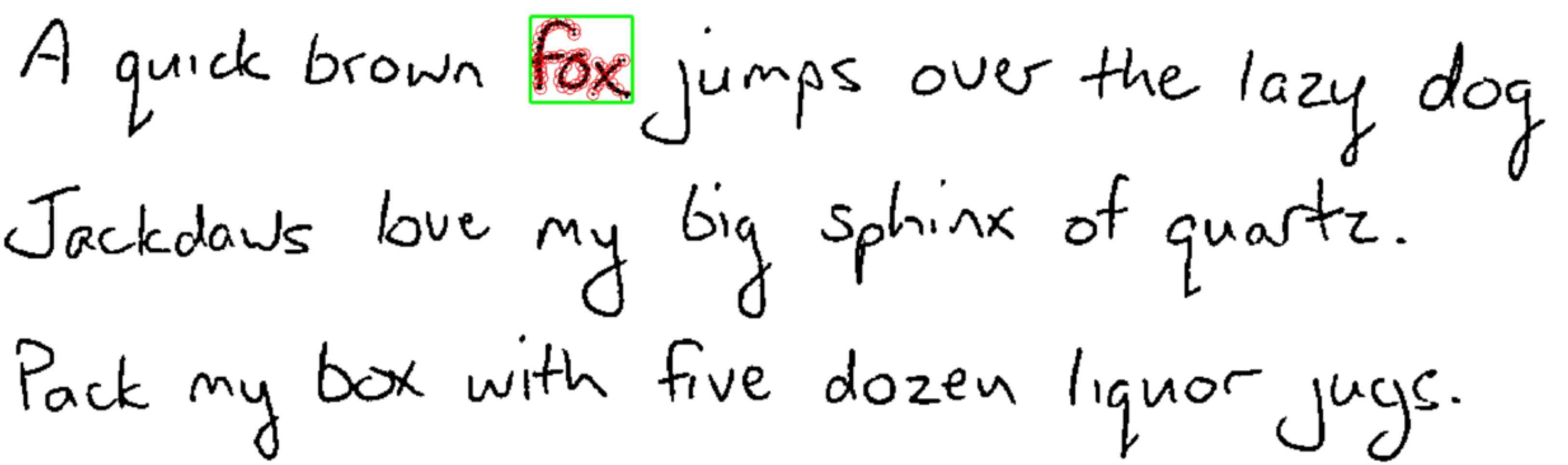
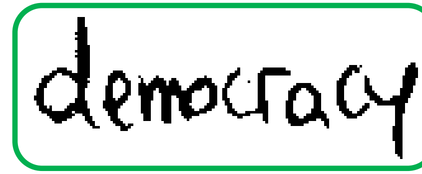
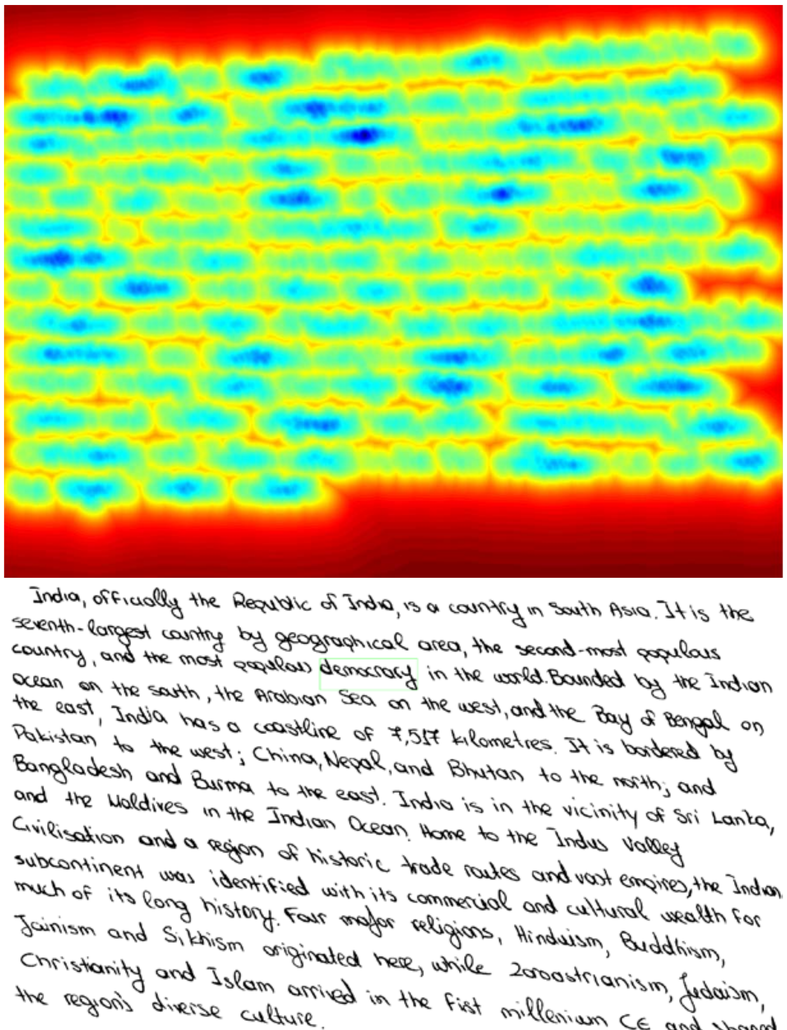
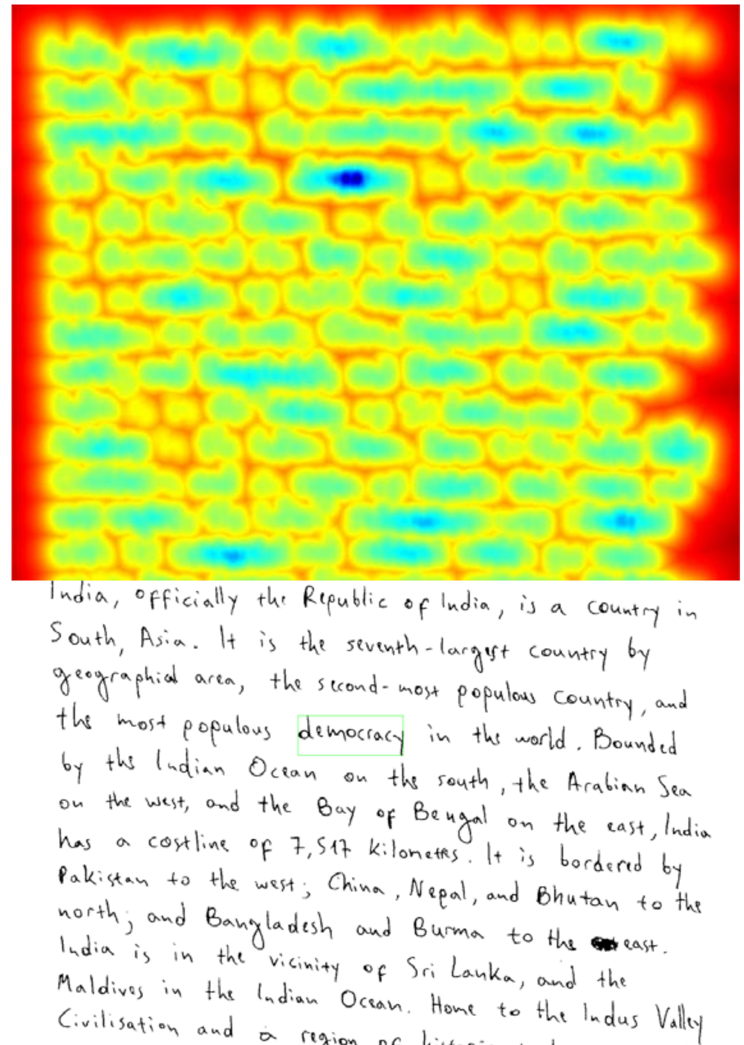


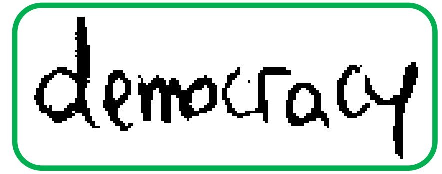
Sample Result: Query = 

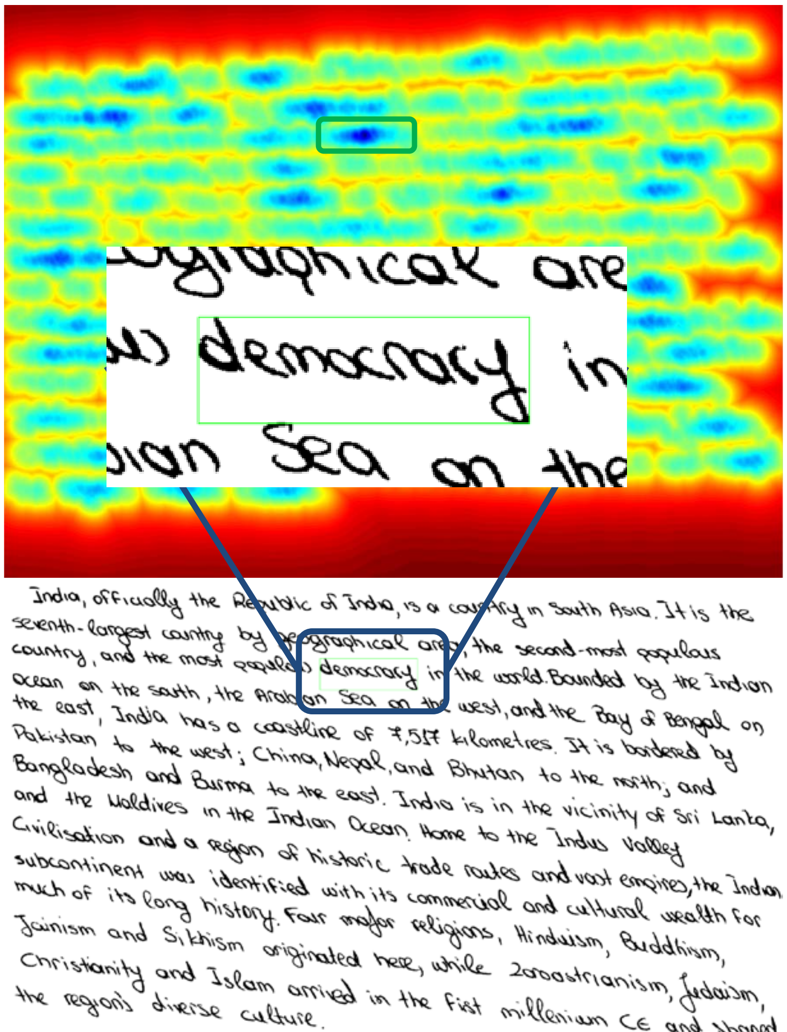


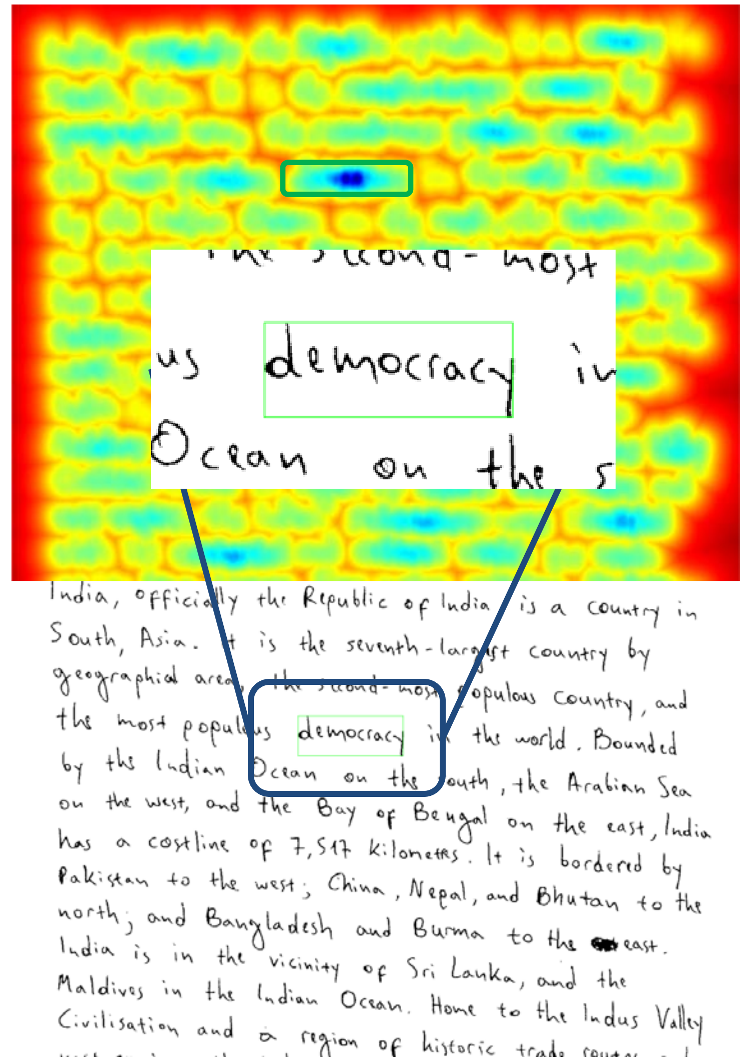


Note: left/right color scales do not match.

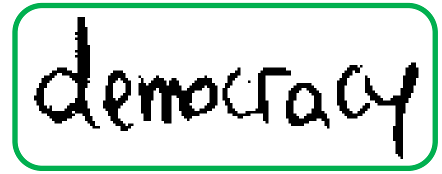
Sample Result: Query =

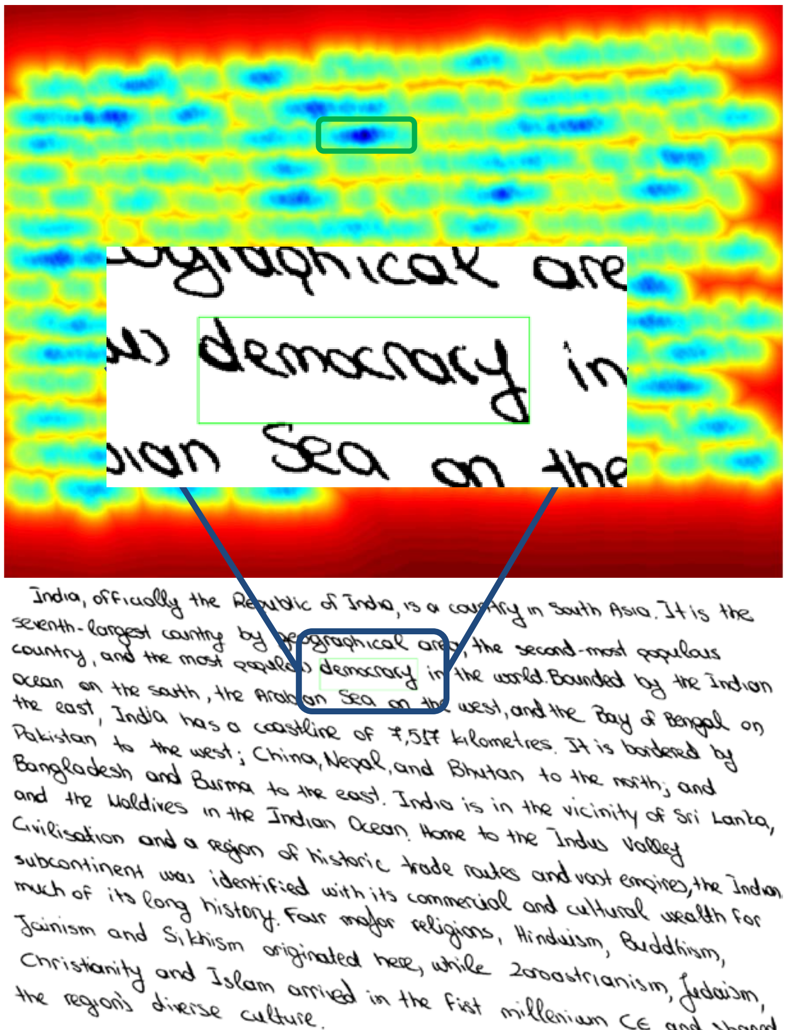


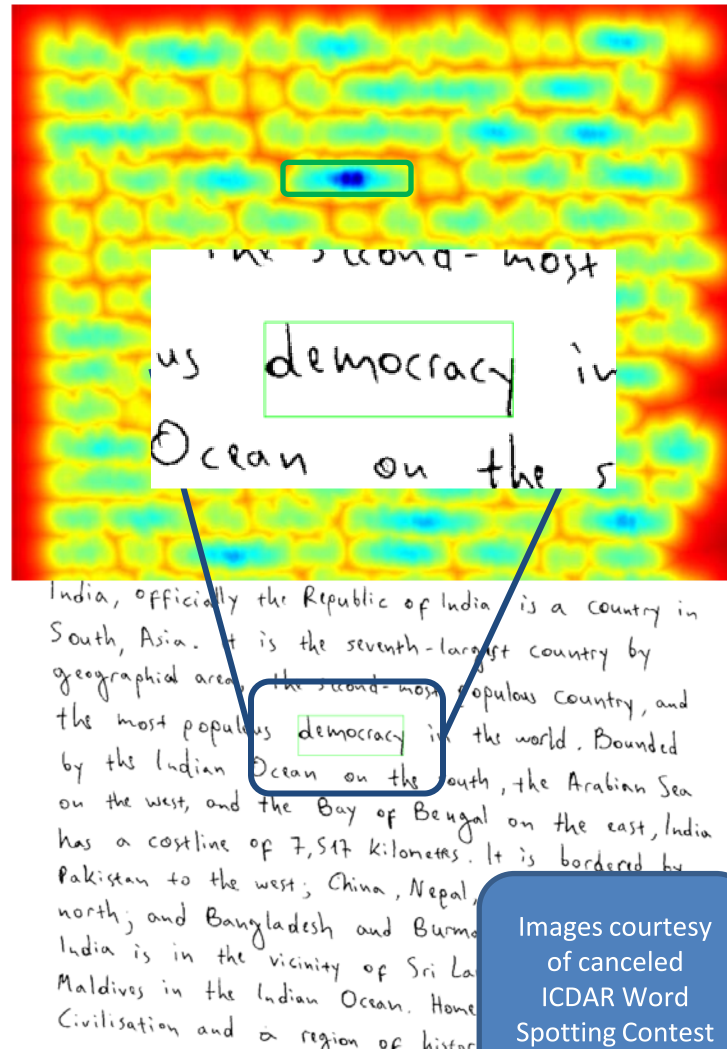




Note: left/right color scales do not match.

Sample Result: Query = 

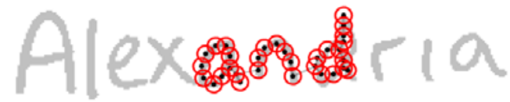
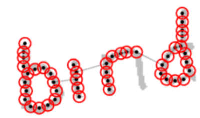


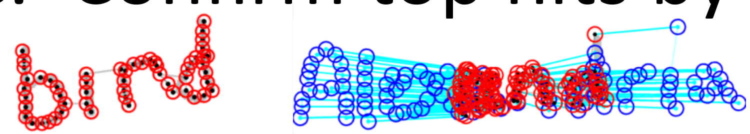


Images courtesy of canceled ICDAR Word Spotting Contest

Note: left/right color scales do not match.

Match Confirmation

- Model matches ink, ignores noise/context
  - Will match **and** to **Alexandria**: 
  - Will match **bird** to **bind**: 
- Whitespace not considered in model
- Expedient heuristic: Confirm top hits by reverse match

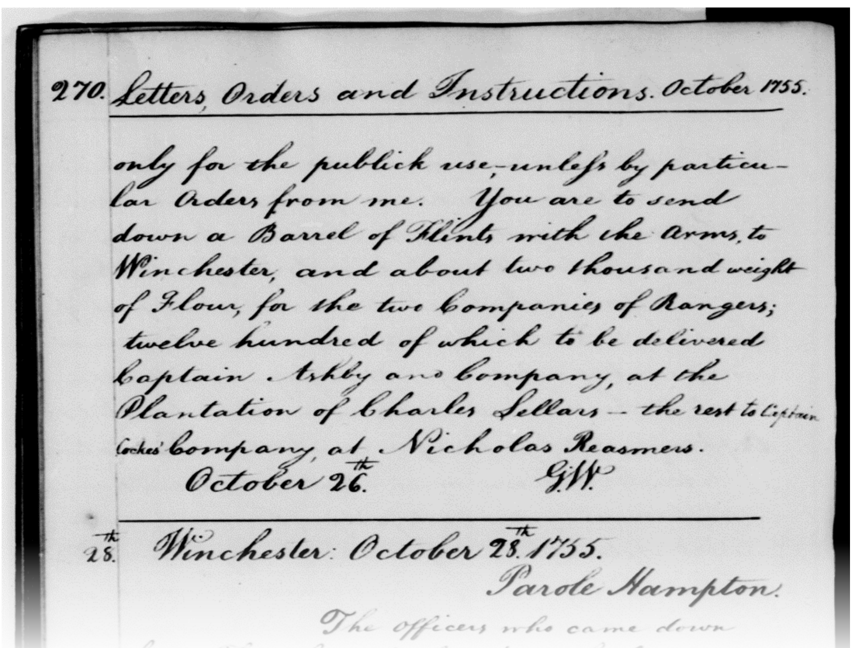


  - Build model of target area & match to query
  - Match energy is greater of the two directions (scaled by number of nodes)

Experimental Data Sets

George Washington (GW20)

- 20 pages; 4685 words
- English cursive script



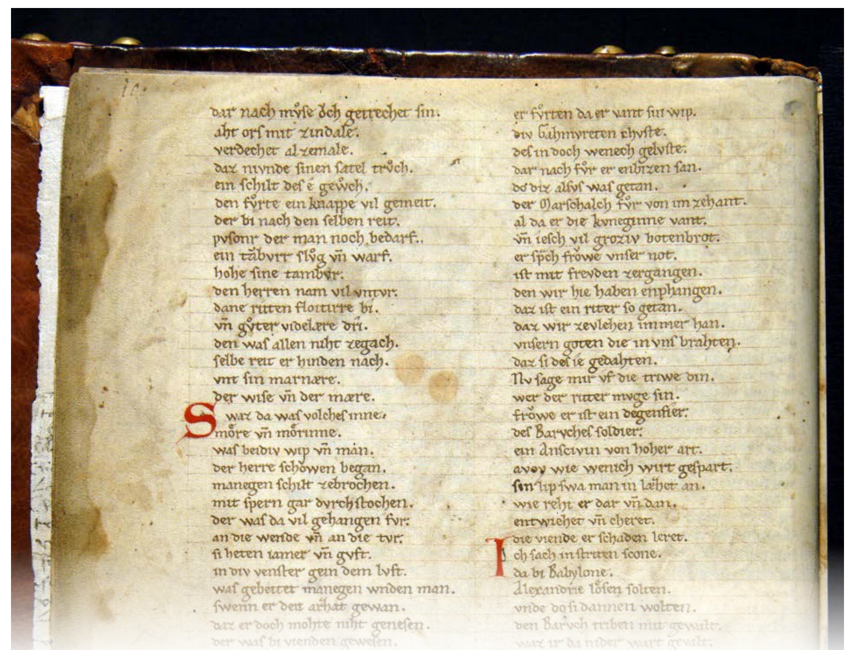
270. Letters, Orders and Instructions. October 1755.

only for the publick use,—unless by particu-
lar Orders from me. You are to send
down a Barrel of Flints with the Arms, to
Winchester, and about two thousand weight
of Flour, for the two Companies of Rangers;
twelve hundred of which to be delivered
Captain Ashby and Company, at the
Plantation of Charles Sellars — the rest to Captain
Cocke's Company, at Nicholas Reasmers.
October 26th. G.W.

28th. Winchester: October 28th 1755.
Parole Hampton.
The officers who came down

Parzival

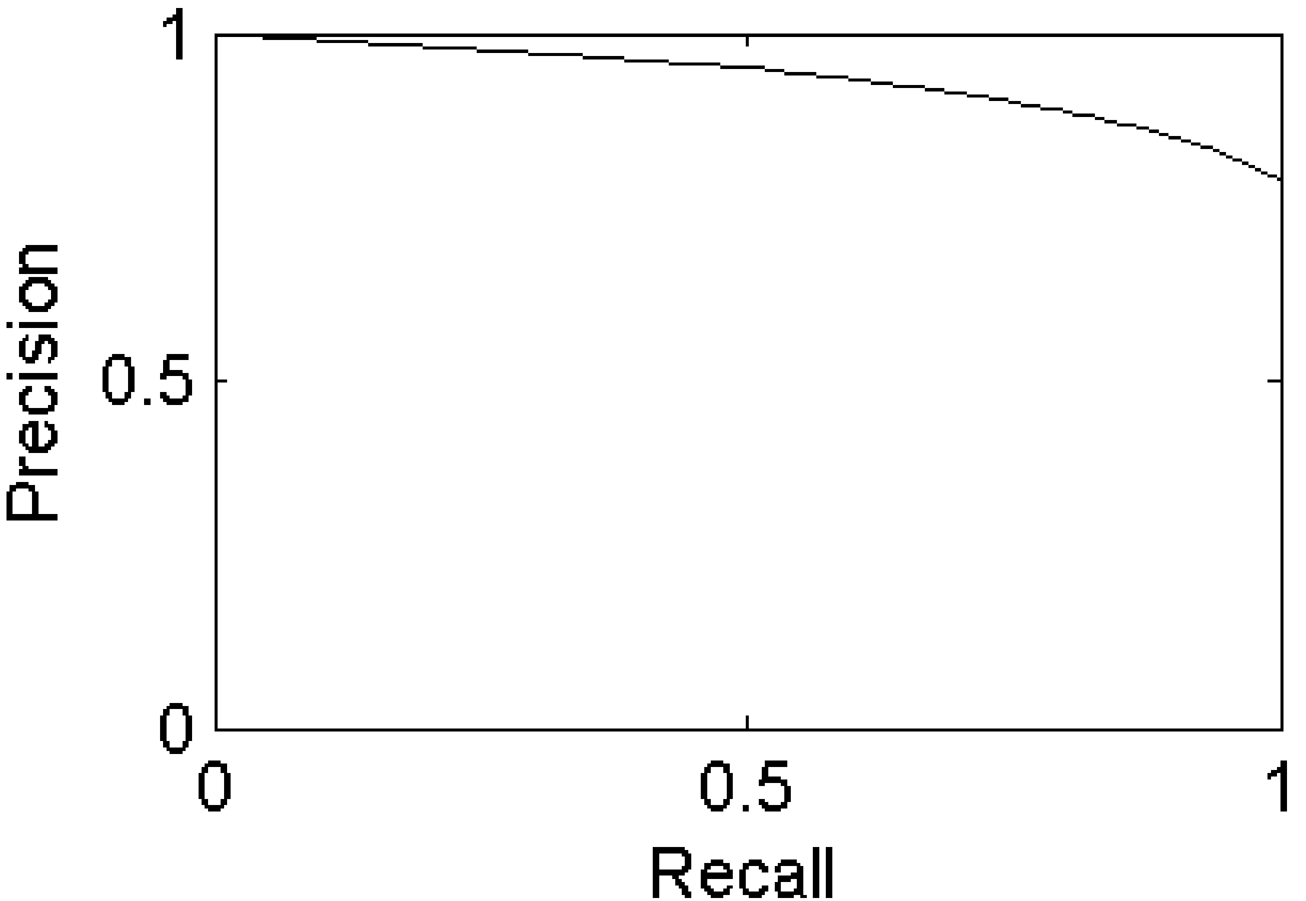
- 47 pages; 18,918 words
- German medieval lettering



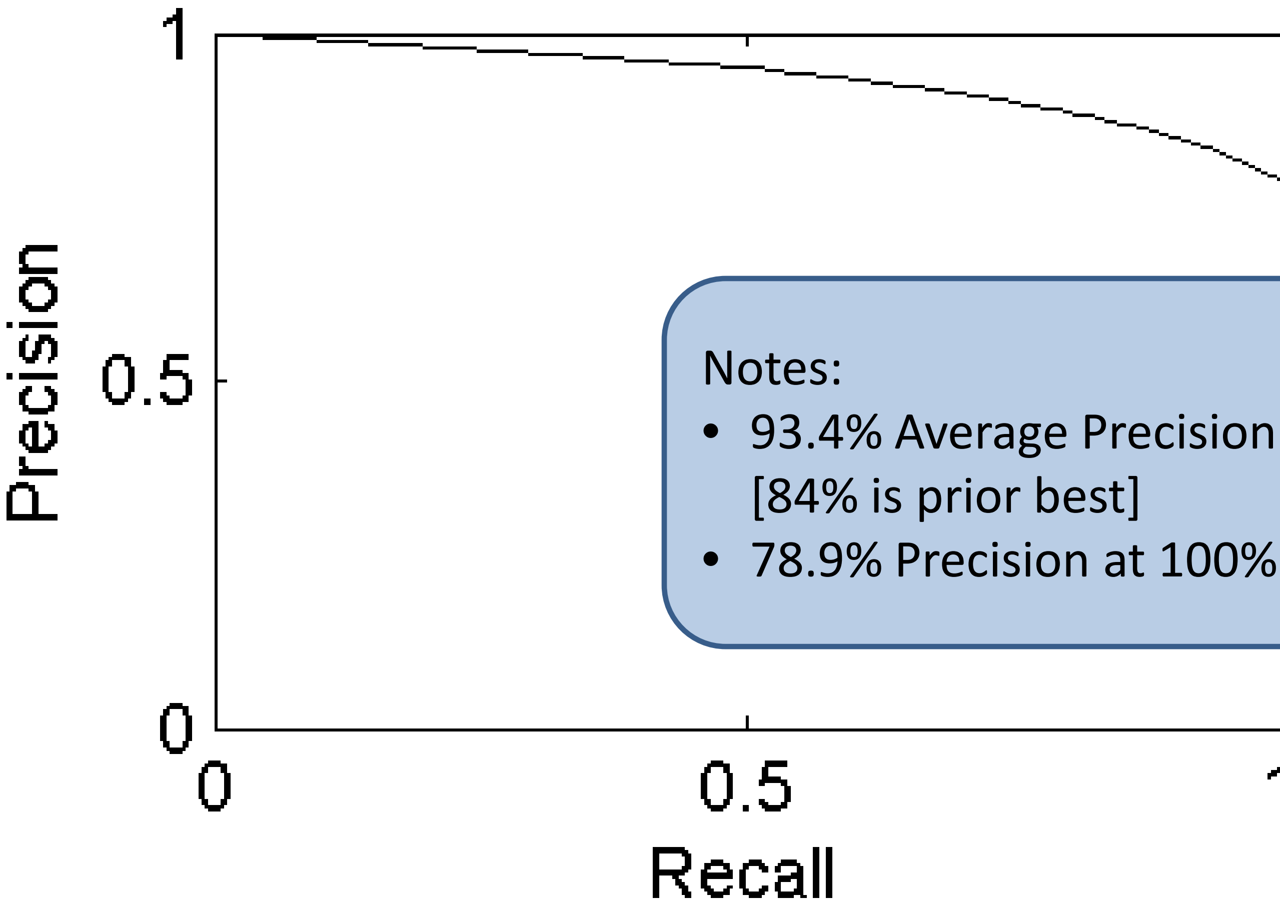
Methodology

- Used train/test split from Frinken et al. [PAMI'12]
- Each non-stopword in training set is a query
  - Some appear multiple times in training set
  - Run retrieval on all instances & take high scores
- Reverse match uses segmented words
- Recall-Precision curves averaged for all queries
  - Threshold may vary from query to query
  - Cross-query calibration still requires research

George Washington

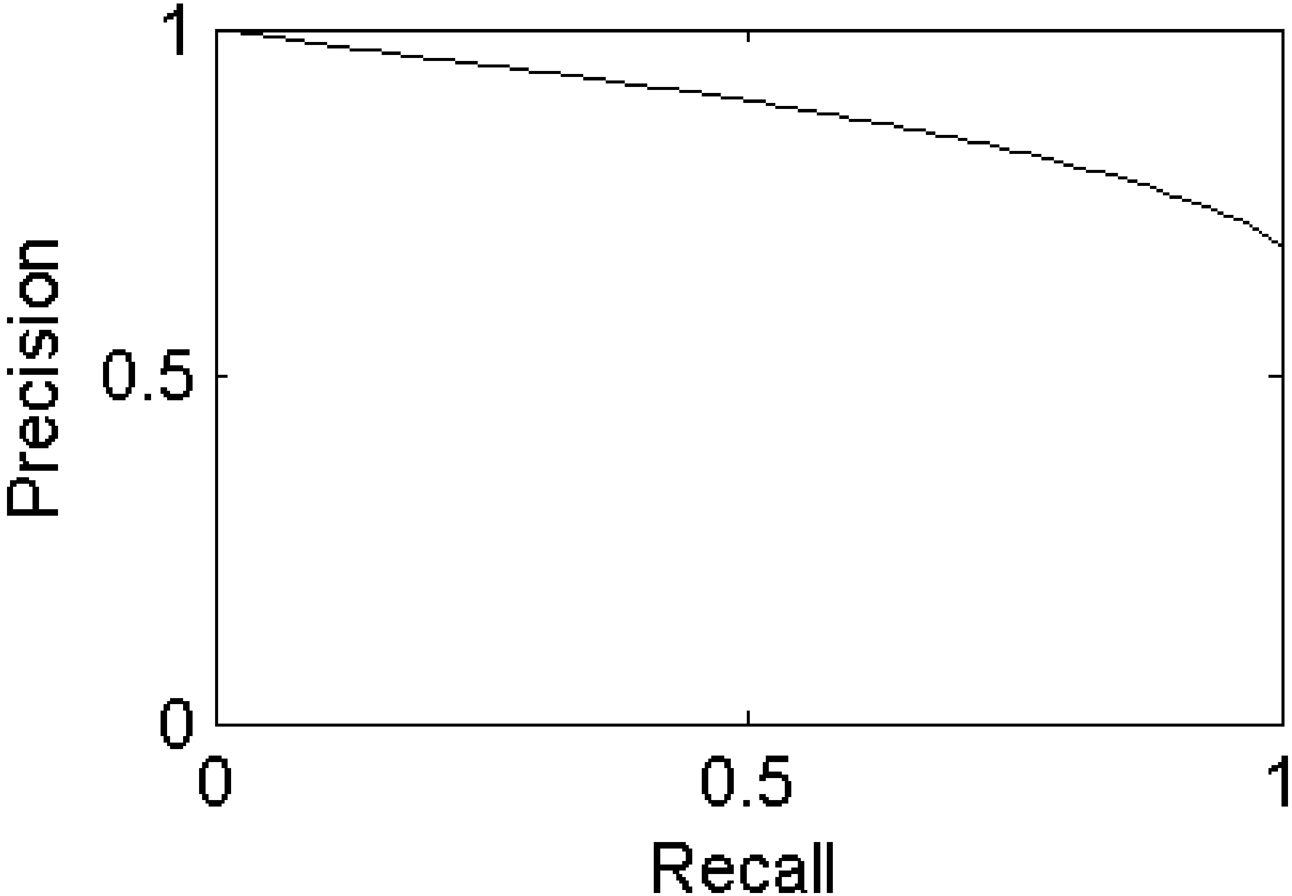


George Washington

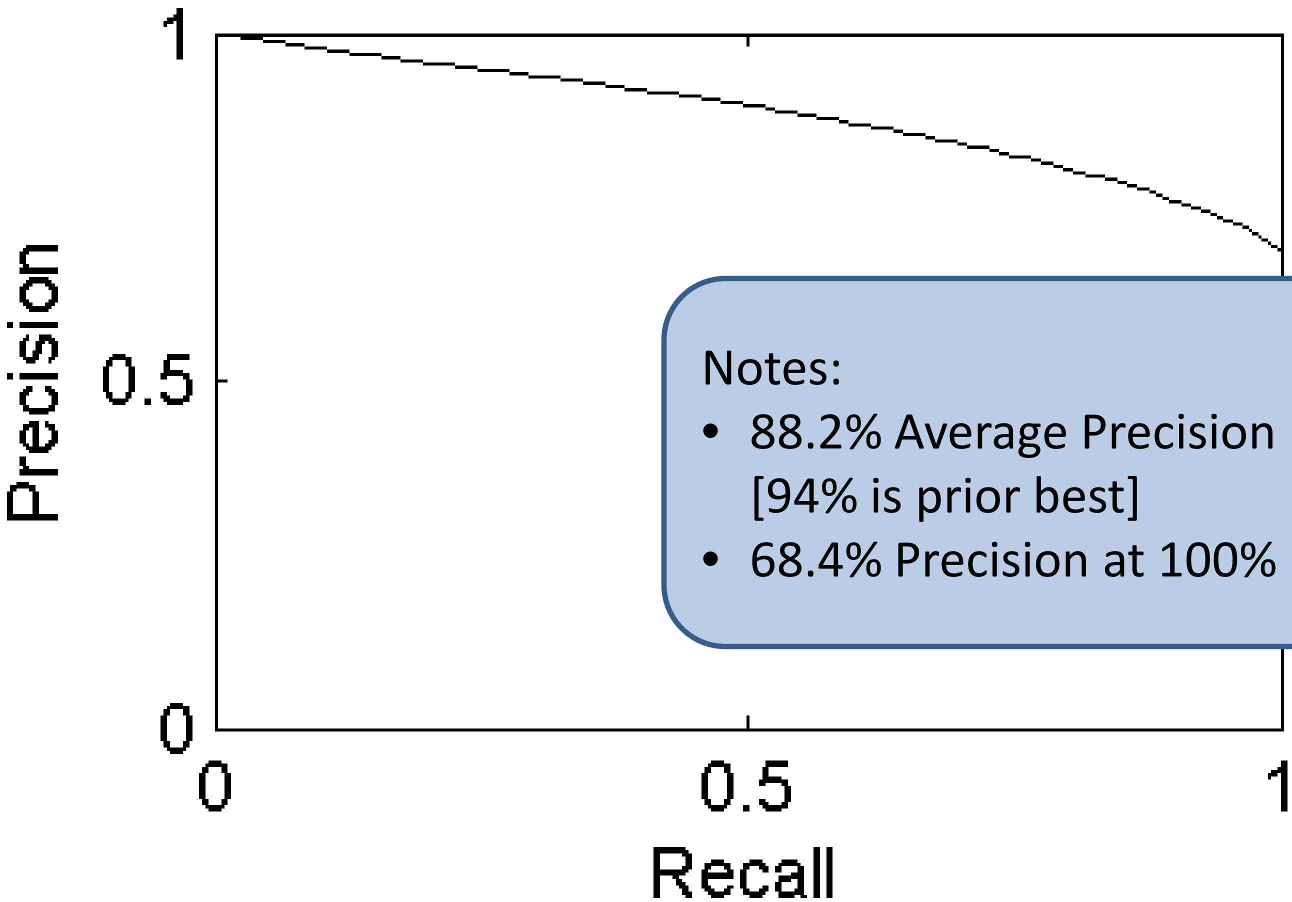


Notes:
- 93.4% Average Precision [84% is prior best]
- 78.9% Precision at 100% Recall

Parzival

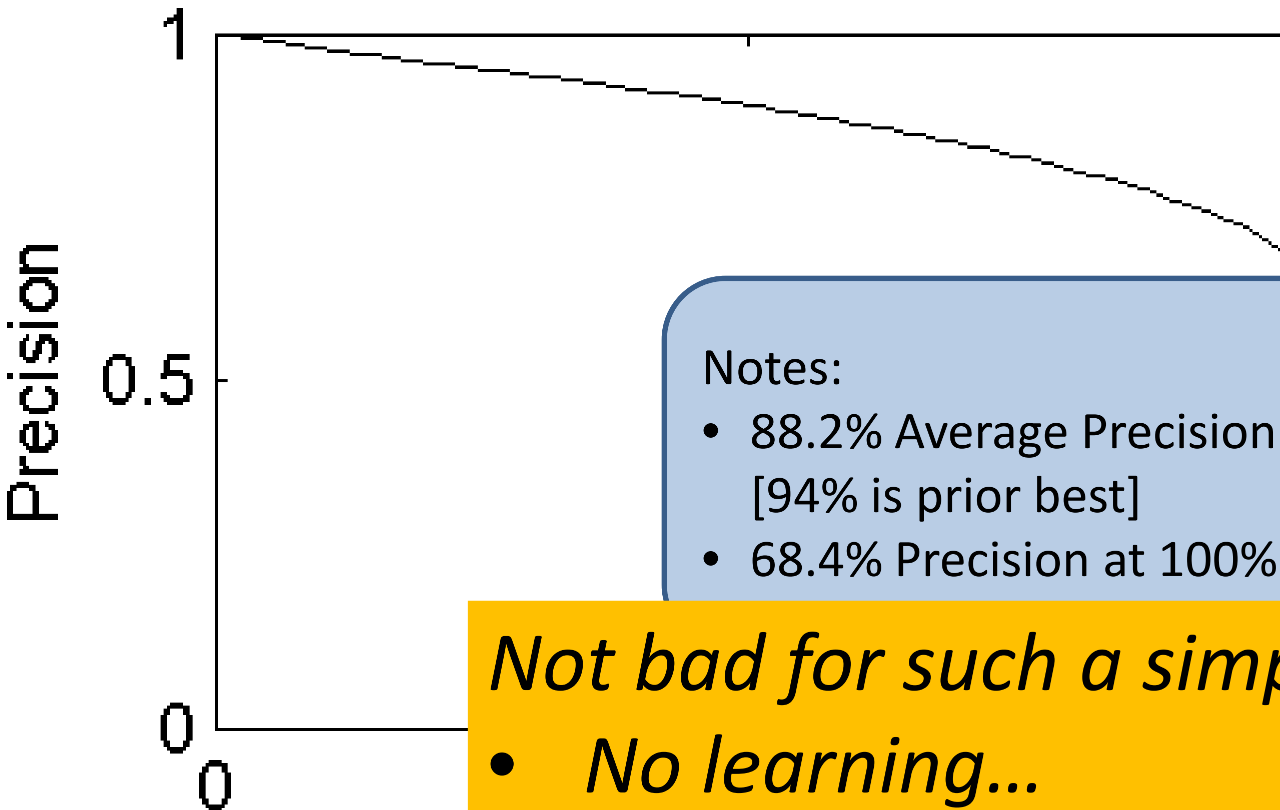


Parzival



Notes:
- 88.2% Average Precision [94% is prior best]
- 68.4% Precision at 100% Recall

Parzival



Notes:
- 88.2% Average Precision [94% is prior best]
- 68.4% Precision at 100% Recall

Not bad for such a simple model!
- *No learning…*
- *No language model…*

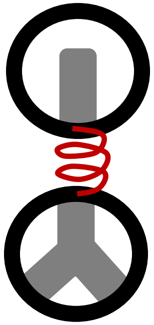
…different yet still good.

Caveat Lector

- Some dependence on handwriting style
  - Intrinsic letter forms can vary
  - Cross-style spotting requires more research
- Limited invariance to scale & rotation
  - Match model scale to text in document
  - Correct skew/rotation prior to spotting

- Speed not yet real-time for large collections
  - Roughly 2 Mpixel/second for most words

Part-Structured Promise



- Powerful matching/retrieval tool
  - Part models could be more complex
- Requires no training, language modeling, etc.
  - Easily applied to new languages, figures, etc.

- Intuitive pixel-level correspondences
  - Starting point for further processing?
- Reference code on my web page
  - I welcome opportunities to collaborate!

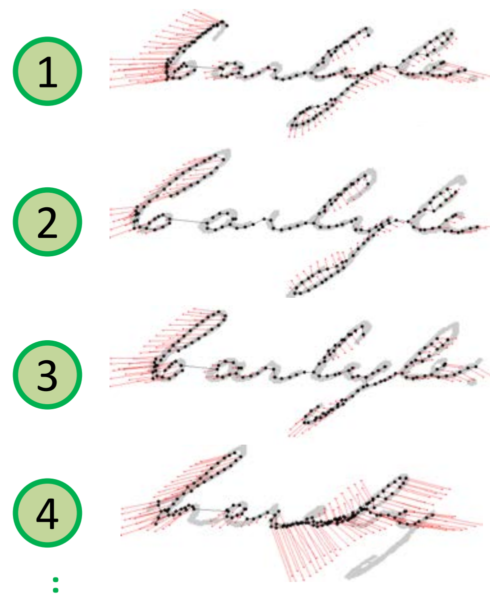
http://cs.smith.edu/~nhowe/research/code/

Thank You

Rare Words

- Performs well with single training examples

Singleton training example



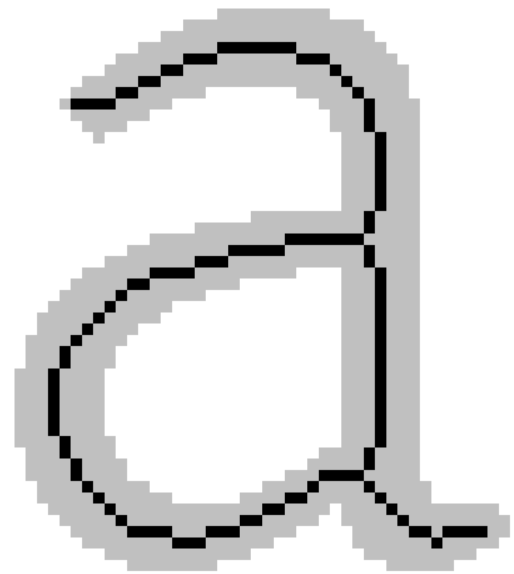
All three instances in target set rank at top of retrieval list

GW20: 25.4% of queries are singletons ➔ 60.2% precision at full recall

Parzival: 31.8% of queries are singleton ➔ 69.5% precision at full recall

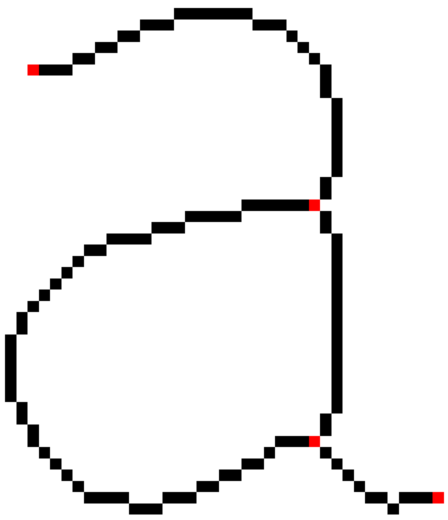
Building PSM from Image

1. Find skeleton



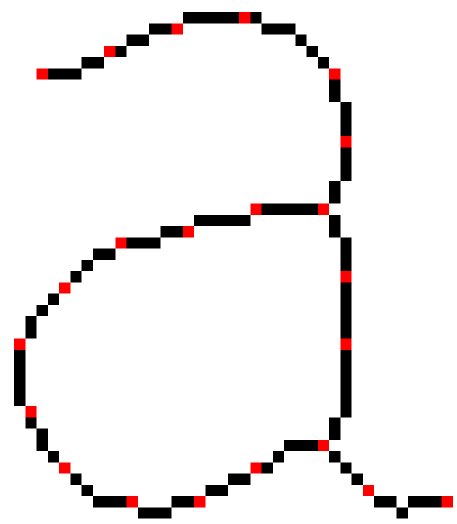
Building PSM from Image

1. Find skeleton
2. Select endpoints & junctions



Building PSM from Image

1. Find skeleton
2. Select endpoints & junctions
3. Add points chosen ***2r*** from included points



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1. Find skeleton
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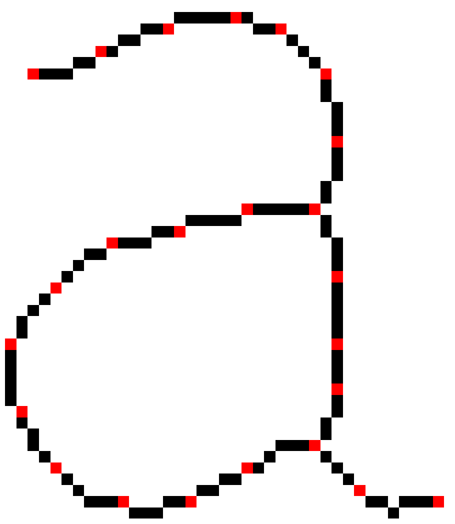
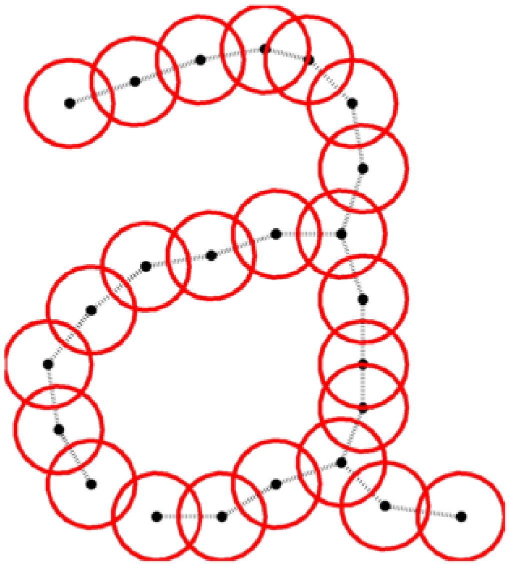
4. Additional points to fill remaining gaps



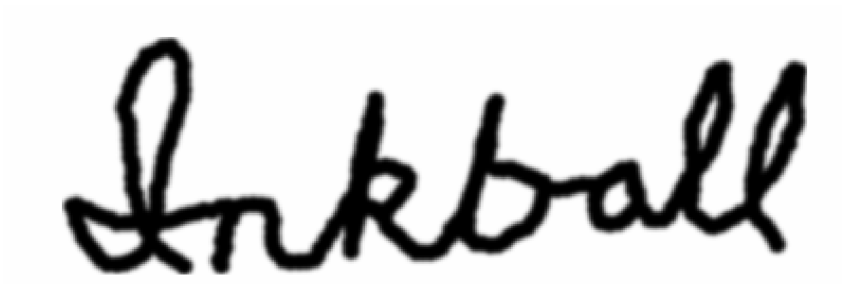
Building PSM from Image

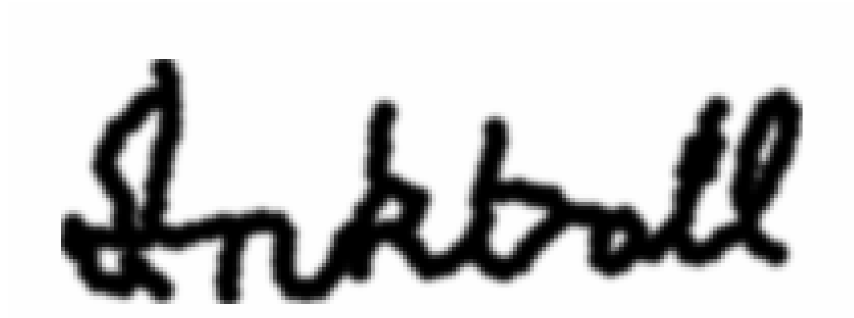
1. Find skeleton
2. Select endpoints & junctions
3. Add points chosen ***2r*** from included points
4. Additional points to fill remaining gaps
5. Form tree by greedily connecting closest pairs



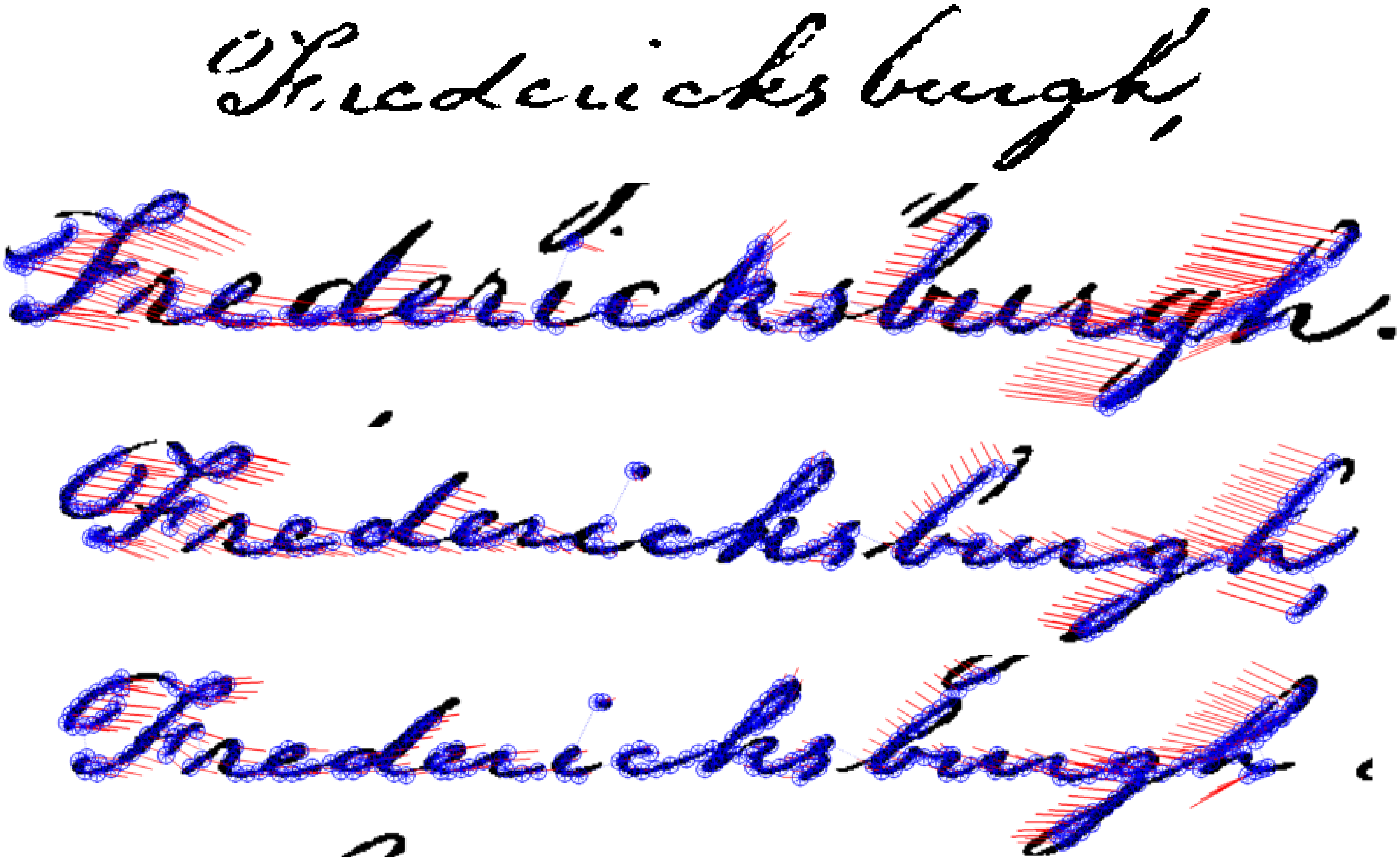
Online vs. Offline Models

- Online query allows model structure to follow actual stroke
- Offline query must use *ad hoc* model structure

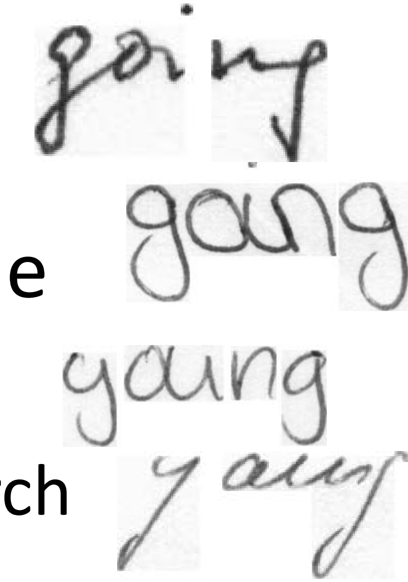




Some Matches



Caveat Lector



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